Collateral, Reallocation, and Aggregate Productivity: Evidence from the U.S. Housing Boom*

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Abstract

This paper shows that rising real estate prices reduce industry productivity, because they lead to a reallocation of capital and labor towards inefficient firms. I establish that the rise in real estate value during the US housing boom relaxes firms' financial constraints. Companies borrow additional funds to invest, hire labor, and increase output. However, firms holding real estate are significantly less productive than non-holders. Rising real estate prices thus reallocate capital and labor towards inefficient firms. This has significant negative consequences for aggregate industry productivity. I find that industries with stronger growth in real estate value see a significant reduction in total factor productivity growth. A 10 % increase in real estate value lowers TFP growth by 0.62 %. The negative effect is driven by misallocation. To shed light on the role of financial sector, I show that banks with superior information about borrowers are better at identifying productive borrowers and supply less credit to unproductive firms when collateral values rise. My results provide direct evidence that financial frictions drive misallocation and suggest a channel for reallocation's falling contribution to growth in recent years.

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1 Introduction

Firms use their real estate as collateral, so rising house prices increase collateral values and relax firms' financial constraints. Corporate finance typically views better access to credit as positive. In early theoretical work, increases in collateral value and credit lead to economic expansion and higher efficiency (Kiyotaki and Moore, 1997; Holmstrom and Tirole, 1997). Recent work shows that real estate booms increase firms' leverage (Cvijanovic, 2014) and investment (Chaney, Sraer and Thesmar, 2012). Other studies, however, cast doubt on the predicted positive effects of higher asset values.[1] During the recent credit boom, fueled by rising real estate prices, total factor productivity (TFP) growth became less cyclical (Wang, 2014; Fernald and Wang, 2016). The contribution of factor reallocation across firms to productivity growth also declined (Decker, Haltiwanger, Jarmin and Miranda, 2016, 2017). So far, we lack empirical evidence that connects changes in firm collateral with aggregate productivity.

This paper shows that rising real estate prices reduce industry productivity, because they lead to a reallocation of capital and labor towards inefficient firms. I construct real estate holdings for a large sample of listed US firms from 1993 to 2008 and show that an increase in real estate value relaxes collateral constraints. Higher collateral value significantly increases firms' debt, investment, and employment. However, I find that real estate holding firms have persistently lower levels of TFP and labor productivity than non-holders. Both facts combined imply that inefficient firms expanded relative to more productive firms. Aggregating to the four-digit industry level, results show that reallocation leads to a significant decline in industry productivity. A 10 % increase in the growth of real estate value reduces TFP growth by 0.62 %. The effect is economically meaningful. Over the sample period, real estate prices grew around 4 % per year and productivity growth averaged 1.75 % annually (Cardarelli and Lusinyan, 2015).

Poor allocation of resources across firms explains results: the covariance between firm size and productivity declines as prices rise. The decline implies that unproductive firms grow faster than productive firms. There is no effect on unconditional mean industry productivity, so the rise in real estate values does not reduce productivity of the average firm. I also find that capital and labor allocation is worse in industries with a high initial dispersion of real estate holdings across firms. For misallocation to play a role, firms' constraints must be relaxed asymmetrically. If each firm has a similar share of real estate out of total assets, there is no dispersion across firms. Rising real estate prices would allow all firms to borrow more to the same extent, there would be no change in firms'

[1] See Schularick and Taylor (2012); Gorton and Ordonez (2016); Borio, Kharroubi, Upper and Zampolli (2016); Richter, Schularick and Wachtel (2017)

relative size, and thus no reallocation. For industries with high dispersion of real estate values I find a significant decline in TFP growth when prices increase ($-1{,}12$ % for a 10 % increase), while industries with low dispersion see only a weak and insignificant decline. Results extend to industries covered in the NBER manufacturing database. For the manufacturing sector, rising real estate prices reduce productivity growth, and also lead to faster growth in employment of low-skilled workers, compared to high skilled workers.

In a final step, I shed light on the role of the financial sector. I show that better informed banks contributed less to the credit boom fueled by rising real estate prices. Banks with superior knowledge about borrower quality rely less on collateral when deciding over new loans. Thus, the sensitivity of firm debt to rising collateral values is lower for firms that borrow from well-informed banks. Specifically, I use syndicated loan market data to construct banks' industry specialization (defined as banks' loan share to an industry).[2] I show that borrowers in banks' main industries receive significantly fewer loans in response to an increase in real estate value. Moreover, specialized banks are better able to funnel funds towards high-productivity firms when collateral values rise. Banks with no specialization are not able to discriminate between high and low-quality borrowers. The importance of banks' borrower knowledge suggests that the rapid geographic expansion of banks into new markets could have fueled the real estate boom and with it a poor allocation of resources.

My findings highlight that the cross-sectional variation in firms' assets, as well as their joint distribution with productivity, matter for aggregate variables. Relative to the existing literature I make two main contributions. I highlight the importance of collateral constraints for the allocation of capital and labor across firms. Thereby, I open up the 'black box' of abstract wedges driving misallocation. My results provide direct evidence that firm-specific distortions, collateral constraints in terms of real estate, lead to reallocation of resources across firms and reduce aggregate productivity. I also offer a unified interpretation of how misallocation reduces cyclicality of productivity and why housing booms are associated with 'bad booms' (Gorton and Ordonez, 2016; Richter, Schularick and Wachtel, 2017). During the 20 years leading up to the financial crisis, rising real estate values relaxed collateral constraints, which shifted resources towards unproductive firms. This, in turn, dampened productivity growth in a period of economic expansion, leading to acyclical TFP and a decline in efficiency. Speaking to literature that highlights the supply side of poor allocation of credit across sectors (see Borio, Kharroubi,

[2]For literature on the importance of banks' specialization on expertise knowledge, screening, and monitoring, see Acharya, Hasan and Saunders (2006); Loutskina and Strahan (2011); Giannetti and Saidi (2017). Ongena and Smith (2001) and Berger and Udell (2002) provide evidence on the role of bank-firm connections in determining loan terms.

Upper and Zampolli (2016); Chakraborty, Goldstein and MacKinlay (2018)), I focus on demand-driven reallocation due to changes in collateral values.

I build on seminal work by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). They sparked an active literature that shows that misallocation of resources explains a large part of differences in productivity and welfare across countries.[3] At the heart of the models are wedges that distort an efficient allocation of labor and capital. Buera and Shin (2013) highlight the importance of financing constraints in misallocating resources and distorting the marginal product of capital. Moll (2014) shows that financial frictions reduce productivity growth and slow down the transition to the steady state. Midrigan and Xu (2014) find financial frictions distort entry and technology adoption decisions, generate dispersion in the returns to capital across existing producers, and thus productivity losses from misallocation. The above papers find that relaxing financial constraints for productive firms improves welfare. Gopinath, Kalemli-Ozcan, Karabarbounis and Villegas-Sanchez (2017) find that, after the introduction of the Euro, capital was allocated towards unproductive firms that saw their constraints relaxed because they benefited from low interest rates. They assume constrained firms to be large firms, which were able to reap the benefits of lower borrowing costs. Overall, literature established that financial constraints matter for misallocation. Yet, there still exists little direct evidence about the origin of constraints and how they interact with the aggregate economy.

I also add to studies analyzing the effects of credit growth on aggregate productivity. Recent work on bubbles emphasizes the importance of fluctuations of collateral value in reallocating resources across agents, but usually assumes an exogenous path of productivity (Martin and Ventura, 2012; Miao and Wang, 2012). Several empirical papers discuss the effect of credit booms using macroeconomic data (Barajas, Dell'Ariccia and Levchenko, 2007; Mendoza and Terrones, 2008). Gorton and Ordonez (2016) show that credit booms lead to sharp increases in output and investment, but often fail to generate improvements in TFP. Schularick and Taylor (2012) look at a large sample of countries from 1870 to 2008 and find that many credit booms lead to financial crises. Aizenman, Jinjarak and Zheng (2016) show that declines in house prices can lead to an increase in productivity. My results are related to recent papers by Borio, Kharroubi, Upper and Zampolli (2016) and Shi (2017), which focus on reallocation of labor and entrepreneurial talent across sectors during credit booms.

A large literature links real estate prices to firm decisions. Eisfeldt and Rampini (2006, 2009) look at the effect of real estate on debt capacity and capital reallocation.

[3]Numerous policy papers use their methodology to gauge the potential welfare gains from better allocation of resources. See, for example, Pagés (2010).

Gan (2007) and Chaney, Sraer and Thesmar (2012) look at the consequences of an increase in real estate prices on firm investment. They find that increases in real estate value lead to significantly higher investment by firms that hold higher amounts of real estate as assets. Cvijanovic (2014) and Yesiltas (2016) find US firms increased their leverage and changed their capital structure in response to an increase in collateral value. Campello and Larrain (2016) show firms in Eastern European countries increased their share of fixed assets and employment when a regulatory change allowed them to pledge a larger fraction of their real estate assets as collateral. Cerqueiro, Ongena and Roszbach (2017) find that a reduction in pledgeable collateral negatively affects firm performance. In a recent paper, Catherine, Chaney, Huang, Sraer and Thesmar (2018) estimate a structural model to quantify the aggregate effects of looser collateral constraints. They find that reallocation explains around 25 % of total welfare gains, but do not take into account a negative correlation between firms' real estate and productivity.

The paper proceeds as follows. Section 2 explains data and variable definitions, Section 3 empirical strategy and identification. Section 4 shows main results on the firm and industry level and provides evidence on poor allocation of resources. Section 5 reports robustness checks and extensions, and section 6 sheds light on the role of the financial sector. Section 7 concludes.

2 Data

I use data on listed companies in the US from 1993 to 2008. Detailed firm level data allows me to address concerns of endogeneity and reverse causality. Thereby I can identify the underlying channel through which changes on the firm level affect the aggregate economy. This section describes data and variable construction.

2.1 Variable Definitions

Firm information is provided by Standard & Poor's Compustat Database (CS). I restrict the analysis to firms with headquarters in the United States and exclude all firms in finance, insurance, real estate, and mining industries, as well as non-operating establishments. All firms must appear for at least three consecutive years and show no gaps. For detailed variable definitions, see section B in the appendix.

Firm Characteristics Main dependent variables are long-term debt, investment, employment, and value added. All dependent variables are standardized by lagged fixed assets (defined as lagged book value of property, plant and equipment), as is standard in the corporate finance literature.[4] I estimate firm f's productivity a on the two digit industry level i for production function $y_{ft} = a_{ft} k_{ft}^{\alpha_i} l_{ft}^{1-\alpha_i}$ with year fixed effects, where y is valued added, k is fixed assets, and l is employment. I estimate capital and labor coefficients on the two-digit level to have a sufficient number of observations for each industry. All variables are deflated with the appropriate industry price indices. For robustness checks, I also use estimation methods developed in Olley and Pakes (1996) and Levinsohn and Petrin (2003), and explicitly include structures as a factor of production.

Firm controls include firm size, defined as log of total assets; market-to-book ratio, defined as the sum of total assets and common shares minus common equity and deferred taxes, standardized by total assets; return on assets, defined as operating income minus depreciation over total assets; and sales growth to proxy for investment opportunities. To measure firm age, I merge my data with CRSP, which reports each company's initial public offering (IPO) date. As IPOs mark an important change in the life of a company, literature uses IPO dates as a standard proxy for firm age. Additionally, I define five different metrics for financial constraints (see Section B).

Real Estate Data I define *structures* as buildings and construction in progress, and *land* as land and improvements. To maximize the sample size, for each firm I take the average across each variable from 1993-1995, when the number of firms reporting real estate increases rapidly. I drop all observations with negative or missing values.[5] I inflate firms' initial 1993-1995 values with state-level real estate price indices. For structures I use the price index for residential housing and for land the price index for residential land (Davis and Heathcote, 2007). To match state and MSA price indices with data in Compustat, I match firms' ZIP and FIPS codes, which can then be merged with the respective state and MSA codes. The main independent variable *real estate value* is defined as the inflated series for structures plus land, standardized by lagged fixed assets.[6]

Two main assumptions underlie the construction of real estate value. When inflating real estate value by state-level house and land prices, I assume that firms' real estate is located in the same state as their headquarters. Chaney, Sraer and Thesmar (2012) and Cvijanovic (2014) confirm with help of firms' 10K files that this is true for a sizeable part of firms in the sample. I also verify that results are robust to using land values

[4]See Chaney, Sraer and Thesmar (2012); Chakraborty, Goldstein and MacKinlay (2018).

[5]For all baseline results, I only include firms already active in 1993. The online appendix shows that including firms entering after 1993 does not alter results.

[6]Land prices increased significantly stronger than house price in the run-up to the crisis. In contrast to Chaney, Sraer and Thesmar (2012) I thus inflate structures and land with separate indices.

as dependent variable.[7] Additionally, I assume that residential real estate prices reflect commercial real estate prices in the same geographical area. Previous research shows the correlation between both series is high and regression results comparable (Gyourko, 2009). Disaggregated commercial real estate prices are confidential and not available to the researcher. For robustness tests, I use commercial real estate price indices for four census regions from 1996 onward, provided by CoStarGroup's *Complete CCRSI data set*. I winsorize all dependent variables and real estate at the 1^{st} and 99^{th} percentile.

Industry Level Industry variables are averages across firms weighted by value added. Growth rates are log differences of averages and winsorized at the 1^{st} and 99^{th} percentile in each year to avoid that outliers drive results. As controls I compute industry sales growth, industry capital-labor ratios, as well as average return on assets and log firm size. The latter control for the fact that some industries are dominated by a few large firms with high return on assets. For every industry I additionally define the following metrics.

Initial dispersion: For reallocation to play role, firms must differ in their real estate as share of total assets. If a rising tide lifts all boats equally, there is no relative shift in firm size and hence no reallocation. Rising real estate values must relax financial constraints asymmetrically within each industry, which requires variation across firms in terms of real estate assets. I define industries *initial dispersion* in real estate value as the standard deviation of average 1993-1995 real estate value across all firms within each industry. I split industries into bottom and top tercile.

Common and allocation component: An additional way to test whether changes in TFP are driven by poor allocation of resources is to decompose industry TFP into[8]

[7]In general, firms' land is geographically more concentrated than structures. Using land values mitigates the potential bias arising from using state level house prices if structures are scattered across the country and not near the headquarter. As land does not depreciate, it also alleviates concerns about the correct adjustment to firms' book value of real estate based on buildings' age. Similarly, I will show that results also hold for manufacturing firms only, which exhibit geographic clustering, unlike firms in the service sector.

[8]For each industry, let $y_i = \sum_{f=1}^{M_i} y_f$, $k_i = \sum_{f=1}^{M_i} k_f$, and $l_i = \sum_{f=1}^{M_i} l_f$ denote industry output, capital and labor as a sum across M_i firms f in industry i. Also, denote industry-wide averages as $\bar{y}_i = \frac{y_i}{M_i}$, $\bar{k}_i = \frac{k_i}{M_i}$, and $\bar{l}_i = \frac{l_i}{M_i}$. Then we can decompose industry TFP A_i into an industry mean, as well as a covariance term:

$$A_i = \frac{y_i}{k_i^\alpha l_i^{1-\alpha}} = \frac{\sum_{f=1}^{M_i}\left[y_f \frac{k_f^\alpha l_f^{1-\alpha}}{k_f^\alpha l_f^{1-\alpha}}\right]}{k_i^\alpha l_i^{1-\alpha}} \frac{M_i}{M_i} = \frac{1}{M_i}\sum_{f=1}^{M_i} \underbrace{\frac{y_f}{k_f^\alpha l_f^{1-\alpha}}}_{A_f} \underbrace{\frac{k_f^\alpha l_f^{1-\alpha}}{\bar{k}_i^\alpha \bar{l}_i^{1-\alpha}}}_{w_f} = \overline{A_f \cdot w_f},$$

Making use of $\overline{u \cdot v} = \bar{u} \cdot \bar{v} + cov(u, v)$, we can decompose the above expression into equation (1).

$$A_i = \underbrace{\left(\frac{1}{M_i}\sum_{f=1}^{M_i}\frac{y_f}{k_f^{\alpha}l_f^{1-\alpha}}\right)}_{\bar{A}_i}\underbrace{\left(\frac{1}{M_i}\sum_{f=1}^{M_i}\frac{k_f^{\alpha}l_f^{1-\alpha}}{\bar{k}_i^{\alpha}\bar{l}_i^{1-\alpha}}\right)}_{\bar{w}_i} + cov(w_f, A_f) = \bar{A}_i\bar{w}_i + cov(w_f, A_f), \quad (1)$$

where w_f denotes the relative weight of firm f, and A_f is firm productivity. $\bar{A}_i\bar{w}_i$ denotes the unconditional industry mean. The latter term $cov(w_f, A_f)$ denotes the covariance between firm size and firm productivity within each industry, which I call the allocation component. If productive firms are also larger, industry productivity is above the unconditional mean, otherwise below. A reallocation in terms of relative weights implies that unproductive firms increase their size and rising house prices should have a negative impact on the covariance term.

NBER manufacturing database Compustat covers large, listed firms, which differ from the average firm in the economy. To increase the external validity of my results, I additionally use the NBER manufacturing database. For each four digit industry, I analyze how changes in the value of structures affect investment, employment and productivity. I additionally analyze the employment effects for low- and high-skilled workers separately. For variable definitions, see Section B. The manufacturing database uses census information and is thus representative of the entire US manufacturing sector.

2.2 Descriptive Statistics

The Compustat firm sample ranges from 1993 to 2008 and comprises 5,478 firms with 48,462 firm-year observations in 349 two-digit industries. The average industry has 36.6 firms per year, with a maximum of 296. For the median firm in the sample, real estate comprises 24 % of fixed assets. In total, 60.2 % of all firms report non-zero real estate holdings. In general, Compustat contains large companies. The median firm is 34 years old and has 662 employees. Table 1 shows summary statistics for the full sample, split into high and low real estate owning firms (defined as bottom and top tercile). Real estate owning firms are larger and older, but significantly less productive. They have a higher capital-to-labor ratio, but lower debt and investment rates.

Figure 1 shows the kernel density plot of log(TFP), conditional on industry fixed effects, with firms split into bottom and top tercile by real estate value. The solid line of firms with high real estate is left of the dashed line for firms with low real estate (as share of fixed assets). Average productivity is lower for real estate holding firms. The difference is highly significant, as I will show below. Importantly, real estate owning firms have persistently lower levels of productivity: the autocorrelation of TFP is 0.8. Table 2 shows summary statistics for the industry level, again split into terciles of real estate. On the industry level, the sample is relatively balanced. Low and high real estate industries have similar values for employment, capital, and capital-to-labor ratio. Low real estate industries have higher growth in investment, labor productivity and TFP.

3 Empirical Strategy

In this section I describe the empirical strategy to identify how changes in house prices affect firm characteristics and subsequently industry aggregates.

3.1 Firm Level

The firm-level baseline regression is

$$y_{f,t} = \beta \cdot real\ estate\ value_{f,t} + controls_{f,t} + \delta_f + \tau_{s\times t} + \epsilon_{f,t}, \tag{2}$$

where $y_{f,t}$ is firm f's debt, investment, employment, or value added in year t, all standardized by lagged fixed assets. $real\ estate\ value_{f,t}$ corresponds to real estate value over lagged fixed assets. $controls_{f,t}$ include firm characteristics log of total assets, return on assets, market-to-book ratio, sales growth, as well as the Kaplan and Zingales (1997) index of financial constraints. Variables δ_f denote firm fixed effects, $\tau_{s\times t}$ time-varying fixed effects at the state and/or industry level. Higher real estate value should relax financing constraints and allow firms to increase their debt levels to expand investment and output. We expect $\beta > 0$. Note that on the firm level, I run level regressions with firm fixed effects. Hence, I look at variation within each firm relative to its average. I interpret my results in terms of changes: an increase in real estate value relative to a firm's mean increases/decreases the respective dependent variable relative to its mean.[9]

Rising collateral value should matter more for financially constrained companies, as it increases the value of pledgeable assets. To test this I interact *real estate value* with different metrics of financial constraints. As measures of financial constraints I consider firms' payout ratio and size; their Kaplan-Zingales (KZ) and Whited-Wu (WW) index (Whited and Wu, 2006), where I split firms into bottom and top tercile; and whether they have an S&P bond rating. The effect is expected to be stronger for constrained firms.

[9] Around 40 % of my firm-level observations report zero real estate value. In growth regressions, I would lose a significant share of my sample.

Various potential problems plague a clear identification of the effect of real estate prices on firm performance and industry outcomes. First, there could be reverse causality. Suppose a very large firm expands investment and hires new employees. The direct demand for real estate through investment, but also the indirect increase in real estate demand through higher demand for intermediate goods or higher wages of households could then lead to increases in house prices. To address the issue, I instrument house prices through local housing supply elasticity, interacted with long-term interest rates (Saiz, 2010; Chaney, Sraer and Thesmar, 2012). The idea is that decreases in long-term interest rates lead to higher demand for housing. How strong house prices react depends on local supply elasticity. If it is cheap to build new houses and increase supply, for example in a city bordering desert, then a decrease in long-term rates will have a modest effect on housing prices. If housing supply elasticity is low, because developable space is limited by mountains or water, the increase in demand will translate into higher prices. For the US sample, I use data on local housing supply elasticity on the MSA level and run the following first-stage regression:

$$P_{t,msa} = \gamma \cdot elasticity_{msa} \times mortgage\ rate_t + \delta_{msa} + \tau_t + \epsilon_{t,msa}, \tag{3}$$

where $P_{t,msa}$ is the residential real estate price index on MSA-level, $elasticity_{msa}$ denotes local housing elasticity at MSA level, and $mortgage\ rate_t$ reflects aggregate shifts in the mortgage refinancing rate, adjusted for inflation. The regression includes MSA (δ_{msa}) and year (τ_t) fixed effects, as well as clustered standard errors at the MSA level. The identifying assumption is that increases in firms' local demand for real estate do not affect the economy-wide mortgage rate and are uncorrelated with supply elasticities.

To control for unobserved demand factors, I include time-varying fixed effects on the state-year and industry-year level. These absorb any common industry and state shocks in each year (Gormley, 2010). Additionally, I follow Mian and Sufi (2014) and categorize industries into tradable and non-tradable sectors according to their geographic concentration (as well as service vs. manufacturing). The intuition is that firms operating in the tradable sector can produce at one location, but sell their products everywhere. Firms in the non-tradable sector need to set up shop where demand is. If local demand raises house prices and demand for goods, firms in the non-tradable sector should increase output by more, as they depend on local demand. For each industry, I construct a Herfindahl index that reflects its share of employment that falls in each state. Industries with high concentration are in the tradable sector, and those with low in the non-tradable.[10]

[10] Highly concentrated non-tradable industries are predominantly food, grocery stores, or IT and garment retailers. Tradable industries comprise various goods that can be shipped and consumed everywhere, for example beverages, dairy or aircraft and parts.

3.2 Industry Level

To test whether the reallocation of resources across firms lowers aggregate productivity, I aggregate my data to the four-digit industry level. All aggregate variables are value added-weighted averages of firm level variables. If real estate owning firms are less productive, industries with stronger increases in firms' real estate values should see a decrease in productivity. I estimate

$$\Delta\overline{log(tfp)}_{i,t} = \alpha \cdot \Delta\overline{real\ estate\ value}_{i,t} + \overline{controls}_{i,t} + \delta_i + \tau_t + \epsilon_{i,t}, \tag{4}$$

where i denotes industry, $\Delta\overline{log(tfp)}$ is the log difference of total factor productivity, and $\Delta\overline{real\ estate\ value}$ is the log difference real estate value of i. Both are industry averages, weighted by firm value added. $\overline{controls}$ are industry sales growth, industry capital-labor ratio, as well as weighted averages of firms' return on assets and size. As above, δ_i denotes industry fixed effects and τ_t are time-varying fixed effects at the two-digit industry level or year fixed effects. We expect that industries with higher real estate growth experience more misallocation and have lower TFP growth, which implies $\alpha < 0$.

The underlying mechanism for relative reallocation is an asymmetric relaxation of firms' collateral constraints. If all firms in one industry have the same real estate value in each year, all would expand equally and there would be no reallocation. Hence, a prerequisite for misallocation is variation in real estate value across firms within each industry. I calculate the initial standard deviation in real estate value across firms ($dispersion_{i,93}$) and estimate equation (4) on subsamples with high and low dispersion, defined as top and bottom terciles. When house prices rise, reallocation should be stronger for industries with higher initial dispersion. Firms with high initial real estate value expand at the expense of firms with low real estate value, which exacerbates poor resources allocation within industries. Industries with little or no dispersion should not suffer from a change in relative weights and hence no misallocation. Thus, α is expected to be strongly negative within industries with high dispersion.

The decline in productivity is driven by an increase in the size of unproductive firms, relative to productive firms. In a counterfactual scenario, I fix firms' size at the beginning of the sample period and shut down the reallocation channel. Industry productivity A_i is a weighted average of firm productivity A_f, so $A_{i,t} = \sum_f \theta_{f,t} A_{f,t}$, where $\theta_{f,t}$ is firms' share of total value added each year. Fixing the share $\theta_{f,t} = \theta_{f,1993}$ at its initial 1993 value gives the effect of rising real estate value on industry productivity when there is no misallocation. Specifically, I estimate

$$\Delta\overline{log(tfp)}_{i,t} = \sum_{t=1993}^{2008} \gamma_t \cdot \Delta\overline{real\ estate\ value}_{i,t} \times year_t + \overline{controls}_{i,t} + \delta_i + \tau_t + \epsilon_{i,t}, \tag{5}$$

where $year_t$ is a dummy with value 1 in the respective year. To run equation (5), I aggregate in two ways: *i*) with time-varying value added shares $\theta_{f,t}$ (*time-varying VA*), and *ii*) with shares fixed at the beginning of the sample, $\theta_{f,1993}$ (*fixed VA*). If reallocation is the driving force of declining productivity growth, estimating (5) under fixed value-added shares should produce non-negative and insignificant coefficients γ_t. The difference between coefficients under both scenarios can then be attributed to reallocation of capital and labor towards inefficient firms.

4 Results

This section first shows that an increase in the value of a firm's real estate increases its long-term debt. Firms use the funds to increase output and expand. In a second step, I explore the effects of the relative increase in size of real estate owning firms on aggregate productivity. The average real estate holding firm has lower productivity than the average non-real estate holding firm. Industries with stronger increases in real estate value see a sharper decline in productivity.

4.1 Firm Level

Table 3 shows that firms that saw a stronger rise in their real estate value also increased in size. An increase in real estate value increases long-term debt, investment, employment, and value added. For each dependent variable, I run a parsimonious regression with firm fixed effects only, as well as one saturated with controls and time-varying fixed effects on the industry and state level.[11] The structure of fixed effects absorbs any common shocks within each industry and state. For each dependent variable, there is a significant positive effect of real estate that is similar across specifications. This highlights that common shocks are unlikely to drive results. A one-dollar increase in real estate value increases long-term debt by 15.4 cents (column (2)), investment by 3.5 cents (column (4)), and employment by 1.6 employees per thousand dollars of fixed assets (column (6)). Finally, also firms' value added increases significantly in columns (7)-(8). Values in brackets denote coefficients when dependent and independent variables are standardized to mean zero and standard deviation of one. Under the full specification, a one standard deviation increase in real estate increases all dependent variables by 0.15-0.20 standard deviations. Note that labor responds stronger than investment. To provide further evidence that rising real estate values relax collateral constraints, the online appendix interacts real

[11] The stepwise addition of controls and fixed effects does not alter the result (unreported).

estate value with different definitions of financial constraints. If rising asset prices work through the collateral channel, they should have a stronger effect on firms that face tighter constraints. For all metrics of financial constraints, the coefficient on the interaction term is significant and positive. In line with theory, rising collateral value has stronger effects on constrained firms

Having established that firms raise new debt in response to an increase in collateral value, which they spend to invest and hire additional employees, Table 4 shows that real estate owning firms have a lower *level* of productivity. I estimate equation (2) with $log(TFP)$ as dependent variable with subsequent addition of controls and fixed effects. I am interested in a comparison across firms, so I do not include firm fixed effects. Column (1) is simple pooled OLS and shows a strong negative correlation between real estate value and productivity. Column (2) includes year fixed effects, and Column (3) time-varying fixed effects at the industry level and thus compares firms within 4-digit industries. All three columns show that firms with higher real estate holdings have significantly lower productivity than their peers with low real estate value. Finally, column (4) controls for firm size and age, results remain similar. For the sample of firms with positive real estate values, moving a firm from the 10^{th} to the 90^{th} percentile reduces productivity by 5.7 % in column (4), or alternatively 11.8 % in column (2).[12] Taken together, the results in Table 3 and 4 show that a rise in real estate value disproportionately relaxes borrowing constraints for low productivity firms, even after controlling for firm size and age, as well as industry characteristics.

Interlude: Why are real estate owning firms less productive? This section established that real estate owning firms have persistently lower levels of productivity. For its negative effect on aggregate productivity, the underlying reason why firms that hold real estate are inefficient does not matter. As long as rising real estate prices allocate capital and labor towards inefficient firms, TFP growth declines. None the less, to shed some light on why productivity and real estate are negatively correlated, Figure 2 offers some suggestive evidence. Panel (a) plots firms' average probability of increasing capitalized leases, buildings, or land against firm age.[13] While young firms are more likely to hold capitalized leases, as they grow older, they are more likely to buy real estate (buildings and land).[14] Panel (b) plots firms' average investment rate and sales growth against firm age. Younger firms have higher investment and growth

[12]Results are robust to alternative metrics of productivity (labor productivity, TFP estimated with Olley-Pakes and Levinsohn-Petrin.

[13]For each firm, I define a dummy equal to 1 if present book value of the asset is higher than last year's, i.e. if the firm buys more of the asset.

[14]The online appendix confirms these descriptive results with regressions. In all regressions, older firms are more likely to hold buildings and land, and less likely to own capitalized leases.

rates, a common finding in the literature (Brandt, Van Biesebroeck and Zhang, 2012; Haltiwanger, Jarmin and Miranda, 2013). While no definite evidence, the picture that emerges is the following: Young firms are productive and fast growing, but do not buy real estate − potentially because they have better outside investment options or not enough capital to finance objects on such large scale. Only at later stages in their life do they increase their share of real estate assets. However, as older firms have lower investment rates and productivity growth (Alon, Berger, Pugsley and Dent, 2017), a higher share of real estate assets coincides with weaker performance. When real estate prices rise, collateral constraints are relaxed for older, but unproductive firms. This being said, after controlling for firm age, real estate owning firms are still significantly less productive.

The effects of misallocation on industry productivity are due to *persistently lower levels* of productivity of collateral-owning firms. Thus, it is important that looser constraints do not lead to an improvement in firms' *productivity growth*. Otherwise, they affect aggregate TFP not only through reallocation *across* firms, but also through changes *within* firms' productivity.[15] Table 5 uses firms' TFP growth ΔTFP_f as dependent variable and shows that there is a weak negative, but mostly insignificant relationship between real estate value and firm productivity (all regressions include firm fixed effects and thus compare within firm changes). Columns (1)-(3) consecutively add fixed effects and controls. Only in column (3) with firm and industry*year fixed effects, as well as controls, an increase in real estate value by one unit (which corresponds to a 100 % increase) reduces TFP growth significantly, by 1 %. However, the effect disappears over time (columns (4)-(6)). Firms do not use additional credit to pursue unproductive investment projects and the effect of changes in *within*-firm productivity on aggregate TFP is negligible. As I will show, industry results confirm that poor allocation of capital and labor reduces growth, which reassures me that a mechanic decline in revenue productivity when collateral constraints are relaxed is not driving aggregate results.

4.2 Industry Level

Section 4.1 established that when firms see a rise in their real estate value, they increase their debt to finance additional investment and production. Real estate holding firms increase their relative share of industry-wide output. Relaxing collateral constraints thereby leads to a reallocation of resources towards unproductive real estate owning firms. This section shows that changes on the firm level have negative aggregate consequences.

Table 6 demonstrates that productivity growth is significantly lower within industries

[15] For literature on loan supply and firm productivity, see Doerr, Raissi and Weber (2017); Duval, Hong and Timmer (2017); Heil (2017).

that see a stronger increase in real estate value. Column (1) uses industry fixed effects. TFP and real estate value have a strong negative correlation. A 10 % increase in real estate growth, which corresponds to 2.5 years, reduces TFP growth by 0.6 %.[16] Column (2) adds year fixed effects, column (3) time-varying fixed effects at the two-digit industry level. The latter absorb common shocks to industries within each two-digit industry cluster. Columns (4)-(6) add industry controls. In all specifications, higher growth in real estate value reduces industry productivity − in the most demanding specification in column (6), a 10 % appreciation of real estate value reduces TFP growth by around 0.62 %.[17]

As explained in Section 3.2, if misallocation lies at the heart of the problem, *i*) the covariance between firm size and productivity within each industry should decline, and *ii*) misallocation should be worse in industries with higher initial dispersion in real estate value across firms. Table 7, columns (1)-(2) use the decomposed elements of productivity, the common and covariance terms, as dependent variables. All variables are standardized to mean zero and standard deviation of one. Column (1) shows that industries with a stronger increase in real estate value see an insignificant fall in their unconditional mean. In contrast, column (2) reports that there is a significant decline in the covariance between firm size and productivity within industries. Thus, unproductive firms increased their size by more.[18] Columns (3) and (4) show the results of estimating equation (4) for industries in the bottom (low disp.) and top (high disp.) tercile of dispersion. While the effect is insignificant and negative in column (3), it is strongly and significantly negative for industries with high dispersion in column (4). A 10 % increase in real estate growth decreases productivity by 1.12 % within industries with high dispersion.

Finally, Figure 4 plots the coefficients of estimating equation (5) for fixed and time-varying value added shares. The short-dashed line under fixed shares is always above zero (coefficients γ_t are positive but insignificant in all but one year), while the long-dashed line for time-varying value added is always below zero (coefficients are negative and significant for half of the years). The solid blue line is the difference between the two. It shows that,

[16] Average growth of the FRED's *All-Transactions House Price Index for the United States* was around 4 % for the sample period.

[17] The online appendix shows that the effect is insensitive to alternative TFP metrics and nearly twice as strong for labor productivity.

[18] A common finding in the literature is that the covariance between firm size and productivity varies significantly across industries. The online appendix shows results for quantile regressions with the covariance (*cov.*) component as dependent variable for the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile. Confirming findings in Table 7, there is a significant negative effect of real estate growth on the covariance term. Rising real estate prices lead to worse allocation of resources within industries with high dispersion (lower percentiles). This suggests that industries that already suffer from poor allocation of capital and labor are hardest hit. In addition, I confirm that the allocation component has a significant positive effect on log(TFP), which further supports the finding that rising real estate prices lead to misallocation and thereby reduce TFP.

when shutting down the misallocation channel, there is no effect of real estate growth on industry productivity. In contrast, if we allow firm size to change with rising real estate value, there is a significant negative effect of real estate growth on TFP growth, which gets stronger over time. Misallocation seems to accelerate on from the early 2000s, when house price growth sped up. This is consistent with a contemporaneous decline in economy-wide productivity growth as found in Decker, Haltiwanger, Jarmin and Miranda (2016). In conclusion, a rise in collateral value increases output of unproductive firms, which leads to misallocation of capital and labor across firms. Consequently, aggregate productivity falls, and more so in industries with larger initial variance in firms' real estate value.

Table 8 shows that results hold true for the NBER manufacturing sample that covers also small firms. An increase in real estate value growth increases industries' investment and employment growth, but reduces productivity growth. As above, for each dependent variable, I run a parsimonious pooled OLS regression, as well as one saturated with controls, industry and year fixed effects.[19] Higher real estate growth increases industries' investment (columns (1)-(2)) and employment (columns (3)-(4)). Focusing on columns (5)-(6), we see that a 10 % increase in real estate growth reduces industry productivity growth by around 0.86 %. The effect is statistically and economically significant and in line with results for the Compustat sample. It is larger in magnitude, which could reflect that small firms (that are not covered by the Compustat sample, but part of the manufacturing database) are more sensitive to house price fluctuations (Fort, Haltiwanger, Jarmin and Miranda, 2013).

Table 9 reports that the increase in employment growth is mainly driven by an expansion of low-skilled workers (column (1)), while the effect is weaker for high-skilled workers (column (2)). Unfortunately, the level of aggregation does not allow for a more detailed analysis, but the shift towards low-skilled workers could potentially reflect misallocation towards firms with a high share of low-skilled workers and low productivity. Finally, columns (3) and (4) decompose productivity into the mean and covariance component for each two-digit industry. The significant decline in the mean suggests that the individual four-digit industry became less productive (as shown above, *within* each industry, resources are allocated towards inefficient firms). The insignificant decline in the covariance component suggests that allocation *across* industries is of second order importance.

Long-run effects To analyze the long-run response of productivity to a shock to real estate values, I estimate a panel VAR using Compustat data aggregated to the industry-

[19]The stepwise addition of controls and fixed effects does not alter the result (unreported).

year level. Specifically, for industry i in year t I estimate

$$Y_{i,t} = A(L)Y_{s,t} + \delta_i + \tau_t + \epsilon_{i,t},$$

where Y is a vector of covariates including industry real estate value (log difference), log(TFP), the covariance component of firm size and firm productivity, and industry sales growth. δ_i are industry and τ_t time fixed effects. $\epsilon_{i,t}$ are innovations (what I will call shocks) to variables in Y. $A(L)$ is a lag operator, where L denotes the number of lags. Based on information criteria MBIC, MAIC, and MQIC I choose a lag of 2.

I am interested in the impulse response function (IRF) of covariance and TFP to real estate price shocks. Using a panel VAR approach has several advantages. First, it allows each industry to have a different underlying structure through industry fixed effects; common shocks to all industries are absorbed through τ_t.[20] Second, ordering of variables by relative exogeneity provides orthogonalized IRFs (OIRF), e.g. the response of productivity to an orthogonal shock in house prices, while holding other variables in the system constant. To this end, I include industry sales growth to control for changes in industry demand. Lastly, panel VARs do not require any functional form for estimation, which allows for high flexibility.

Getting OIRFs requires an ordering of variables by *relative* exogeneity. The first variable affects the following variables contemporaneously and with a lag. The second variable affects the following variables contemporaneously and with a lag, but the first with a lag only, etc (so variables are ordered by relative exogeneity to each other). As first variable, I choose industries' real estate values. I showed above that rising house prices affect productivity through reallocation contemporaneously. It is reasonable to assume that, if reallocation changes house prices through changes in aggregate productivity, it will do so with a lag. As second variable, I include industry sales growth as a proxy for demand. Changing collateral values might affect demand through different channels (input-output linkages, local spillovers, etc), so including sales growth will ensure that the responses of TFP and covariance are not driven by contemporaneous demand shocks. I remain agnostic about the relative ordering of covariance and productivity.[21]

Figures 3 shows cumulative orthogonalized impulse response functions of log(TFP) in panels (a) and (b), and the unconditional industry productivity mean, as well as the allocation component in panels (c) and (d). Thin lines denote 90 % confidence intervals. Panel (a) shows a persistent negative effect of real estate growth on industry productivity. The effect is significant for four years. Panel (b) splits the industry sample into industries

[20] I use a Helmert transformation to control for industry fixed effects. For details, see Love and Zicchino (2006).

[21] The ordering of TFP and covariance has no effect on results (unreported).

with low (black line) and high (blue dashed line) initial dispersion in collateral values across firms. In line with findings above, the negative effect in panel (a) is entirely due to industries with high initial dispersion. Finally, panels (c) and (d) show that there is no effect on unconditional industry productivity, but a strong and persistent negative effect on the covariance term. Panel VAR regressions thus confirm the main findings for the industry level OLS and fixed effects regressions in section 4.2, and show that there are persistent negative effects of rising collateral values on industry productivity through resource allocation.

5 Robustness

Addressing Endogeneity Concerns Table 10 shows results for the instrumental variable regression (3). Column (1) reports the first stage and a highly significant effect of the instrument on real estate prices. Columns (2)-(5) show that all baseline results hold true for instrumented house prices (real estate is standardized). Firms that see a stronger increase in instrumented real estate value expand more, but have lower productivity.[22] Additionally, in the online appendix, real estate values are inflated by census region commercial real estate prices. The correlation between state-level house price index and commercial real estate prices at the regional level is 0.86. Results are similar to baseline findings in terms of sign, size, and significance.

Changes in real estate prices could also be driven by high consumer demand. If demand for real estate rises hand in hand with demand for goods, then changes in demand drive increases in debt and investment, as well as in real estate value. I use a battery of time-varying fixed effects at the state and industry level in the baseline regressions. State*year (industry*year) fixed effects absorb all unobserved time-varying characteristics that vary at the state (industry) level. Thus, the identifying assumption is that each year demand changes equally for all firms within each state (industry). Results in Table 3 show that coefficients are insensitive to the inclusion of fixed effects.

Additionally, I follow Mian and Sufi (2014) and categorize industries into tradable and non-tradable sectors according to their geographic concentration (or service vs. manufacturing). The intuition is that firms operating in the tradable sector can produce at one location, but sell their products everywhere. Firms in the non-tradable sector need to set up shop where demand is. If local demand raises house prices and demand for

[22]In Column (1) the corresponding F-statistic is 22.76. and the incremental R^2 equals 0.06. Comparing coefficients of IV and non-IV MSA-level regressions, coefficients are about 40 % larger under the instrumented specification, which suggests that firm demand for inputs and labor does not drive increases in real estate value.

goods, firms in the non-tradable sector should increase output by more, as they depend on local demand. For each industry, I construct a Herfindahl index that reflects its share of employment that falls in each state. Industries with high concentration are in the tradable sector, and those with low concentration in the non-tradable.[23] Table 11 shows that effects are similar for tradable and non-tradable industries classified by geographic concentration in columns (1)-(2), and service vs. manufacturing in columns (3)-(4).[24]

Davidoff (2015) raises the concern that migration of skilled workforce to geographically attractive areas could raise property prices, as well as human capital, and invalidate supply elasticity as an instrument. If highly skilled and well paid workers prefer to live in scenic areas with lakes or mountains, firms face higher property prices and a workforce with high human capital. If firms with high real estate values are located in "supercities", while those with low real estate values lie in areas with low human capital, this could bias results.[25] To address the issue I focus on MSAs with a similar number of firms with and without real estate. I categorize MSAs according to their absolute distance in the number of real estate owning firms minus non-owners, standardized by total number of firms in the MSA. MSAs with a high (low) value of distance have a high (low) share of real estate owning firms. MSAs with intermediate distance values have similar shares. Under the assumption that workers do not discriminate among firms based on their real estate onwership, changes in human capital affect all firms within the same MSA equally. Table 11, columns (6)-(7) show that results hold even within narrowly defined MSA areas. They use long-term debt as dependent variable, and restrict the distance of firms' real estate value to lie in the 10^{th} to 90^{th} and 25^{th} to 75^{th} percentile bracket in each MSA (results extend to investment, employment, and value added). Higher real estate value leads to significantly more long-term debt by firms in areas with similar human capital. Finally, column (5) uses a permanent sample of firms active over the full sample period, to avoid selection effects through exit. Results remain stable.

Online Appendix The Online Appendix provides further extensions. It shows that

- effects found in my main regressions map to the standard Hsieh and Klenow (2009) framework of dispersion in marginal products: industries with high variation in collateral values across firms see a strong increase in the dispersion of marginal

[23] Highly concentrated non-tradable industries are predominantly food, grocery stores, or IT and garment retailers. Tradable industries comprise various goods that can be shipped and consumed everywhere, for example beverages, dairy or aircraft and parts.

[24] I only show effects on long-term debt, but results hold for employment and investment.

[25] On the industry level, this would work against my results. If migration by better skilled workforce increases productivity for firms in areas with strong house price increases, the negative effects of misallocation from non-owning to owning firms would be understated.

products of capital.

- estimates are robust to alternative TFP estimation methods, as well as including housing as a factor of production
- effects of rising real estate prices on firm debt and output are stronger for financially constrained firms
- including firms that entered after 1993 does not change main results, i.e. that cohort effects and the changing composition of publicly held firms (driven by the IT sector during the 1990's) do not significantly alter results
- an improving industry covariance between firm size and productivity also increases industry productivity
- rising house prices not only increase employment, but also local industry wages, which could lead to negative spillovers through factor linkages on firms that do not own collateral

6 The Role of the Financial Sector

Previous sections established that inefficient firms borrowed more during the housing boom. In turn, they increased their output and relative weight in the economy. This triggered a reallocation of resources towards inefficient firms that reduced industry productivity. In this section, I take a closer look at the role of the financial sector. I establish that banks with superior monitoring technology or information about firms contributed less to the credit boom. Specifically, borrowers in banks' area of expertise (measured by industry specialization) have a lower sensitivity of debt with respect to increases in collateral value. In other words, if a bank knows the quality of a firm, collateral is less important for firms' access to credit.

Detailed syndicated loan market data on the firm-bank-year level allows me to analyze the effect of bank specialization on loan supply. Syndicated loans are issued jointly by a group of banks to a single borrower. A lending syndicate entails at least one lead bank, which assesses the quality of the borrower, as well as other participating banks. Lead banks negotiate the terms and conditions of each loan and also monitor the borrower while the loan is active. Compared to other types of bank lending syndicated loans are on average bigger in volume, issued to large borrowers, and often used to diversify credit risk. Dealscan provides exhaustive information on transactions, including the issuing syndicate of banks and borrowing firm, outstanding amount, maturity, and interest rates. Additionally, it provides information on firms' and banks' type, location, and industry.[26]

[26]Total syndicated lending increased from about 500 billion U.S. Dollars in 1990 to a peak of nearly five trillion U.S. Dollars in 2007. It is a major source of financing for many large US companies.

To allocate loan portions of transactions I split up the loan facility on a pro-rata basis among all participating banks in the syndicate.[27] I remove transactions with deal status 'canceled'. Total outstanding loan volume is calculated as the sum of the value of all outstanding loans that a firm has from a bank in a given year. All loans are kept active until maturity. I then standardize firms' total outstanding loan volume by lagged fixed assets and winsorize at the 1^{st} and 99^{th} percentile each year.

Bank specialization Banks specialize – a common finding is that banks have better information about firms in their main industries, compared to firms in industries that lie outside banks' area of expertise (Acharya, Hasan and Saunders, 2006; Loutskina and Strahan, 2011; Giannetti and Saidi, 2017). To measure industry specialization on the bank-4-digit industry-year level I use syndicated loan market data to define:

$$specialization_{b,i,t} = \frac{\sum_{f=1}^{F} loan_{b,f,t}}{\sum_{i=1}^{I} \sum_{f=1}^{F} loan_{b,f,t}}, \tag{6}$$

where $loan$ denotes loan volume between bank b and firm f in year t. The numerator sums across all loans by bank b to firms f in industry i – it represent the total loan volume by bank b to industry i in year t. The denominator equals total bank lending in year t to all firms across all industries I. $specialization$ reflects the yearly share of loans extended by each bank to a given industry. For each year, I classify bank-industry pairs into top and bottom tercile by specialization, and define the dummy $specialized_{b,i,t}$. It equals 1 if banks' loan share (as measured by $specialization_{b,i,t}$) to industry i is in the top tercile for any given year, and 0 if it is in the bottom tercile. I then run the following set of regressions:

$$\begin{aligned} loan_{f,b,t}/assets_{f,t} &= \beta_1 real\ estate\ value_{f,t} + controls_{f,t} + \epsilon_{f,b,t} \\ &\quad \text{if} \quad specialized_{b,i,t} = 0/1 \end{aligned} \tag{7}$$

$$\begin{aligned} loan_{f,b,t}/assets_{f,t} &= \beta_1 real\ estate\ value_{f,t} + \beta_2 specialized_{b,i,t} \\ &\quad + \beta_3 real\ estate\ value_{f,t} \times specialized_{b,i,t} + controls_{f,t} + \epsilon_{f,b,t} \end{aligned} \tag{8}$$

$loan/assets$ denotes syndicated loan volume between firm f and bank b in year t, standardized by firm fixed assets. All regressions absorb industry shocks through industry*year fixed effects. Additionally, I control for unobservable changes in loan supply (to isolate demand effects) through bank*year fixed effects. Finally I control for firm characteristics through firm fixed effects, as well as firm controls size, return on assets, and Tobin's q. Each regression uses clustered standard errors at the state-year level. If collateral is more

[27] I keep lead arrangers and participating banks in the sample. I want to contrast specialized banks with superior information with non-specialized banks. Keeping lead arrangers only introduces the problem that arrangers tend to be better informed about borrowers in the first place. However, using lead arrangers only yields qualitatively similar results (unreported).

important for firms if banks have little information about them, we expect that loan volume reacts stronger for firms outside of banks' main industries. This is, β_1 is smaller if $specialized = 1$, or $\beta_3 < 0$.

Results in Table 12 show that loan volume responds by less if a firm borrows from a bank that is specialized in the firm's industry. Column (1) replicates the baseline regression on the loan level and shows that loan volume increases by 23.8 cents in response to a one dollar increase in collateral value.[28] Columns (2) and (3) split the sample into non-specialized and specialized industries. The effect of rising collateral values on loan volume is about 2.5 times higher if a borrower is in an industry outside of banks' expertise. This result is confirmed when I include an interaction term instead of splitting the sample in column (4). The significant and negative coefficient on $real\ estate\ value_{f,t} \times specialized_{b,i,t}$ shows that loan volume increases by 14 cents less within specialized industries, when collateral increases by 1 dollar. Finally, for robustness column (5) employs firm*bank fixed effects and uses only variation within each bank-firm combination. Coefficients remain highly significant and increase in magnitude. Results in Table 12 suggest that better informed banks rely less on collateral values when making lending decisions.

The effect of productivity I argue that specialized banks are better at identifying productive firms, irrespective of collateral values. To test this, I analyze whether the sensitivity of firms' debt with respect to collateral value depends on firm productivity. I run the following regression:

$$\begin{aligned} loan_{f,b,t}/assets_{f,t} =& \gamma_1 real\ estate\ value_{f,t} + \gamma_2 real\ estate\ value_{f,t} \times productivity_f \\ & + controls_{f,t} + \epsilon_{f,b,t} \quad \text{if} \quad specialized_{b,i,t} = 0/1, \end{aligned} \tag{9}$$

where *productivity* denotes average firm productivity across the sample period, split into three (50) percentiles. I run regression equation (9) separately for firms in non-specialized and specialized industries.[29] Hypotheses are that a) lending responds more to increases in collateral value for firms in non-specialized industries, b) the sensitivity of lending to an increase in real estate values is higher for high productivity firms, and c) the latter effect is stronger within specialized industries. The reasoning is as follows. In general, banks in specialized industries have superior screening and monitoring technologies and thus rely less on collateral when deciding to grant a loan. However, for a given relaxation in collateral constraints, the effect on debt should be stronger for high productivity firms, as they can make better use of funds. Finally, if non-specialized banks can only imperfectly discriminate between high and low productivity firms, while specialized banks can do so,

[28] Note that coefficients reflect loan demand, as loan supply is controlled for through time-varying fixed effects on the bank level.

[29] Note that *productivity* is constant for each firm and thus absorbed by firm fixed effects.

an increase in collateral value should lead to higher borrowing for high productivity firms, especially if firms operate in banks' main industries. Relating this to equation (9), γ_1 is expected to be larger in non-specialized industries, while γ_2 is expected to be larger in specialized industries.

Table 13 shows results for regressions equation (9). In line with hypotheses, debt responds stronger to increases in real estate value for firms outside of specialized industries. Columns (1) and (2) use productivity terciles, (3) and (4) 50 percentiles. For both productivity metrics, high productivity firm's debt reacts stronger to increases in real estate value in non-specialized industries (coefficient on *real estate value*). The positive coefficient on the interaction terms suggest that high-productivity firms borrow more in response to an increase in real estate value. However, the effect for high-productivity firms is weaker in non-specialized industries, confirming hypothesis c). Hence, not only do better-informed banks rely less on collateral values when granting a loan, but they are also better able at discerning whether a borrower is of high or low quality.

Following deregulation and technological improvements, banks expanded geographically in the years prior to the 2009 crisis. While the number of banks decreased, the number of branches per bank increased. This is also reflected in banks' deposit diversification, which increased steadily until 2007.[30] Recent research suggests that expanding banks rely of information-insensitive collateralized loans when entering new markets (Loutskina and Strahan, 2011). This likely reflects that they have inferior screening and monitoring ability compared to banks that are already present in a market and thus have existing relationships with borrowers. Hence, banks' geographic expansion increases the importance of collateral in making loan decisions. As firms with a higher share of collaterlizable assets are less productive, banks' geographic expansion likely exacerbated poor allocation of resources.

7 Conclusion

I show that changes in property prices affect firm decisions and aggregate productivity through the collateral channel. During the US real estate boom from 1993 to 2008, firms with a stronger rise in their real estate value increased debt, investment, and output. As real estate owning firms are significantly less productive than non-owners, the relative increase in the importance of unproductive firms triggered relative reallocation and re-

[30]Combining data provided by the FDIC's Statistics on Depository Institutions and Summary of Deposits, I compute bank diversification as 1 minus the Hefindahl index of deposit concentration. The latter reflects each bank's share of deposits that falls into each county.

duced aggregate productivity. Over a 2.5 year period, a 10 % increase in real estate value shaves off about half a percent of industry TFP growth. The covariance between firm size and firm productivity declines and the share of low-skilled workers within an industry increases. Results are similar for a sample of large listed US firms and the universe of US manufacturing firms.

My findings provide direct empirical evidence for a firm-level friction that affects aggregate productivity. Following pioneering work by Hsieh and Klenow (2009), so far most studies on resource misallocation rely on abstract capital and output wedges to quantify the effects of reallocation. Evidence on which frictions or distortions drive reallocation and how they work over time is still scarce. My empirical evidence on the importance of the collateral channel for reallocation sheds light on the 'misallocation black box'. It highlights that the joint distribution of firms' productivity and asset holdings matters for the evolution of aggregate variables.

My results also suggest one potential explanation of why productivity became less cyclical over the last two decades and why the contribution of resource reallocation across firms to aggregate TFP growth declined (Wang, 2014; Fernald and Wang, 2016; Decker, Haltiwanger, Jarmin and Miranda, 2016, 2017). The misallocation of resources towards inefficient firms during an upswing depresses aggregate productivity growth despite rising overall economic output. An open question left to future research is whether the house price collapse and ensuing great recession was able to undo misallocation. While recessions can have a cleansing effect (Caballero and Hammour, 1994), evidence for Europe suggests that this was not the case during the recent crisis (Borio, Kharroubi, Upper and Zampolli, 2016).

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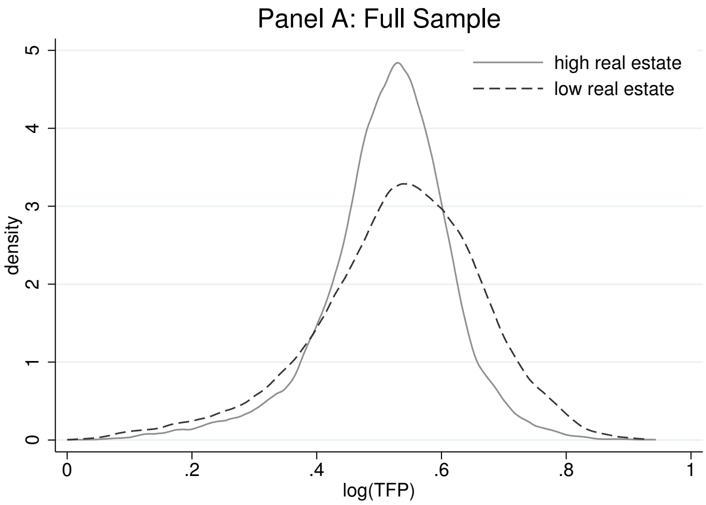
A Figures and Tables

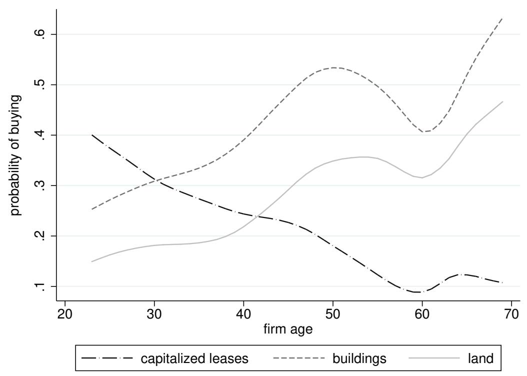
Figure 1: **Productivity**



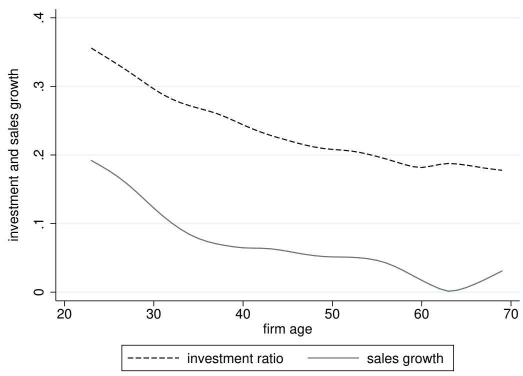
Note: $log(TFP)$ is log of total factor productivity estimated on the the two-digit industry level for production function $y = Ak^{\alpha}l^{1-\alpha}$. *high real estate* and *low real estate* denote top and bottom tercile of firm real estate value distribution. TFP is standardized to mean zero and variance one and conditional on industry fixed effects. *Full Sample* comprises all observations from 1993-2008.

Figure 2: **Real estate, firm age, and efficiency**

(a) Probability of buying real estate by firm age



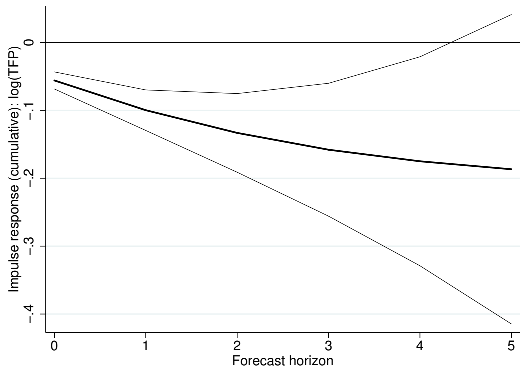
(b) Firm performance by firm age



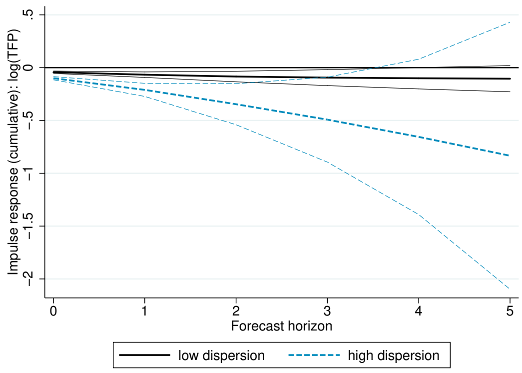
Note: Panel (a) plots firms' average probability of increasing capitalized leases, buildings, or land against firm age. Panel (b) plots firms' average investment rate and sales growth against firm age

Figure 3: **Cumulative OIRF to real estate shock**

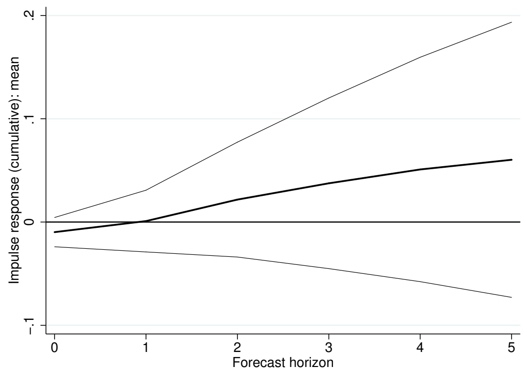
(a) log(TFP)



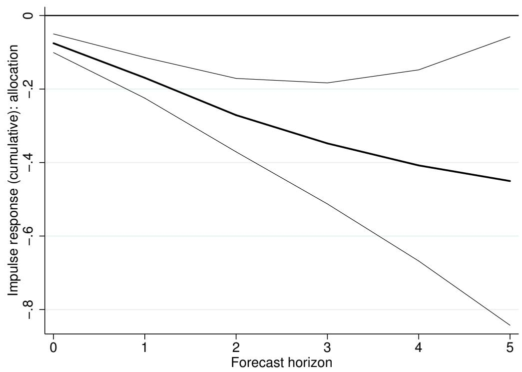
(b) log(TFP) by dispersion



(c) unconditional mean



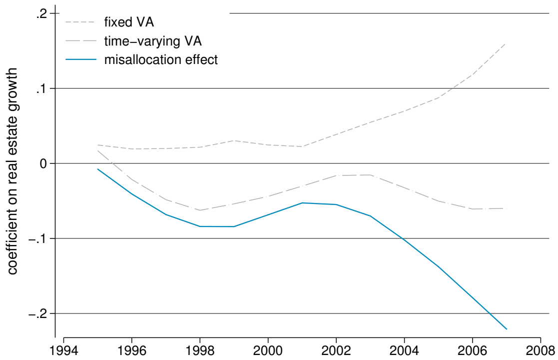
(d) covariance



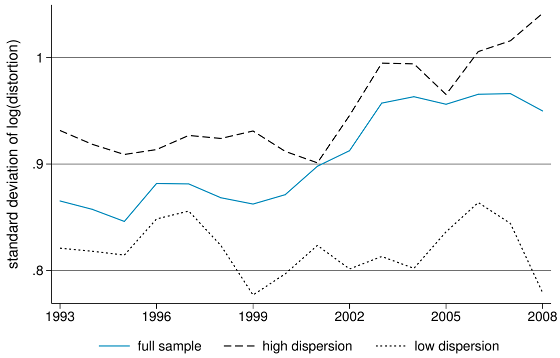
Note: Orthogonalized IRFs with 90 % confidence intervals. Response of industries' firm size and firm productivity covariance (allocation) and log(TFP) to a shock in real estate growth. Panel VAR regressions include industry and year fixed effects. *allocation* and *log(TFP)* standardized to mean zero and variance one.

Figure 4: **Misallocation and Dispersion over time**

(a) Effects of misallocation over time



(b) log(TFP) by dispersion



For variable definitions see section B. Left: Industry level effect of Δ*real estate* on Δ*TFP*, conditional on industry and year fixed effects, over time. y-axis denotes coefficient of Δ*real estate*, interacted with year dummies. *fixed VA* fixes firms' weights as value added in 1993, *time-varying VA* allows for time-varying weights. *misallocation effect* is the difference between both lines. Series smoothed with HP filter ($\lambda = 5$). Each regression includes industry and year fixed effects, as well as controls for sales growth, capital-labor ratio, average firm size and return on assets. Right: Yearly median of within industry-year standard deviation of log distortions. log (distortions) refers to the residual of a regression of *ln(k/l)* on industry-year dummies. *dispersion* stands for dispersion in initial real estate value, split into top and bottom tercile.

Table 1: **Firm: Summary statistics by group**

	(1) **high RE** mean	sd	(2) **low RE** mean	sd	(3) **mean diff** t
real estate value	1.47	(1.46)	0.00	(0.00)	133.32
long-term debt	0.38	(0.90)	0.76	(1.43)	-28.60
investment	0.21	(0.16)	0.39	(0.24)	-77.66
labor	0.06	(0.07)	0.11	(0.10)	-53.51
log(TFP)	0.52	(0.16)	0.57	(0.19)	-20.86
employees	9775.93	(31659.67)	908.60	(4451.87)	36.23
log(assets)	5.13	(2.12)	3.45	(1.76)	79.59
leverage	0.29	(0.91)	0.26	(1.17)	2.68
return on assets	0.04	(0.22)	-0.14	(0.39)	54.12
market-to-book ratio	1.82	(1.49)	2.84	(2.53)	-44.45
sales growth	0.08	(0.32)	0.15	(0.55)	-14.49
Kaplan-Zingales index	0.89	(2.06)	0.83	(2.76)	2.53
Whited-Wu index	-0.25	(0.12)	-0.15	(0.11)	-80.07
Observations	16154		17620		33774

Note: For variable definitions see section B. Growth rates are log-differences. *high RE* and *low RE* denote top and bottom tercile of firm real estate value distribution. *mean diff* is t-value for difference in means. All variables are value-added weighted averages for the four-digit industry level.

Table 2: **Industry: Summary statistics by group (Compustat)**

	(1) high RE		(2) low RE		(3) mean diff
	mean	sd	mean	sd	t
real estate value	0.85	(0.79)	0.50	(0.46)	12.94
employment	99.10	(213.95)	115.31	(257.07)	-1.60
capital	6375.94	(19099.44)	7110.87	(20194.56)	-0.88
capital-labor ratio	65.61	(81.76)	61.27	(72.65)	1.31
return on assets	0.11	(0.05)	0.12	(0.05)	-6.23
investment	0.21	(0.10)	0.25	(0.11)	-8.14
Δ real estate	0.28	(0.34)	-0.34	(0.35)	41.97
Δ investment	-0.01	(0.33)	-0.03	(0.31)	1.15
Δ labor	0.02	(0.32)	-0.12	(0.33)	10.31
Δlp	0.00	(0.29)	0.06	(0.29)	-4.13
Δtfp	0.01	(0.27)	0.04	(0.27)	-2.87
Observations	1096		1097		2193

Note: For variable definitions see section B. Growth rates are log-differences. *high RE* and *low RE* denote top and bottom tercile of firm real estate value distribution. *mean diff* is t-value for difference in means. All variables are value-added weighted averages for the four-digit industry level.

Table 3: **Debt, investment, and labor**

VARIABLES	(1) long-term debt	(2) long-term debt	(3) investment	(4) investment	(5) labor	(6) labor	(7) value added	(8) value added
real estate value	0.199***	0.268***	0.026***	0.035***	0.017***	0.016***	0.359***	0.303***
	(0.019)	(0.021)	(0.002)	(0.002)	(0.001)	(0.001)	(0.026)	(0.033)
	[.117]	[.157]	[.128]	[.177]	[.208]	[.201]	[.181]	[.153]
market-to-book ratio		-0.006		0.015***		0.004***		0.115***
		(0.007)		(0.001)		(0.000)		(0.016)
log(assets)		0.468***		0.024***		-0.005***		0.162***
		(0.024)		(0.003)		(0.001)		(0.030)
return on assets		-0.281***		0.024***		0.025***		9.327***
		(0.071)		(0.008)		(0.002)		(0.350)
sales growth		0.352***		0.036***		0.027***		1.048***
		(0.029)		(0.003)		(0.001)		(0.079)
Kaplan-Zingales index		0.124***		-0.007***		-0.002***		-0.089***
		(0.009)		(0.001)		(0.000)		(0.013)
Observations	48,462	48,430	48,462	48,430	47,372	47,305	31,457	31,056
Adjusted R-squared	0.385	0.435	0.385	0.438	0.633	0.682	0.521	0.644
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	-	Yes	-	Yes	-	Yes	-	Yes
State*Year FE	-	Yes	-	Yes	-	Yes	-	Yes
Cluster	State*Year	State*Year	State*Year	State*Year	State*Year	State*Year	State*Year	State*Year

Note: For variable definitions see section B. Values in parentheses denote standard errors, in brackets coefficients for standardized dependent and independent variables. Growth rates are log-differences. Industry∗Year and State∗Year FE are time-varying fixed effects on the four-digit industry and state level. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Productivity**

VARIABLES	(1) $log(tfp)$	(2) $log(tfp)$	(3) $log(tfp)$	(4) $log(tfp)$
real estate value	-0.051***	-0.070***	-0.042***	-0.034***
	(0.008)	(0.008)	(0.007)	(0.006)
firm age				0.2***
				(0.007)
log(assets)				0.076***
				(0.002)
Observations	31,613	31,613	31,278	31,278
Adjusted R-squared	0.003	0.027	0.263	0.636
Year FE	-	Yes	-	-
Industry*Year FE	-	-	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year

Note: For variable definitions see section B. $log(TFP)$ is log of total factor productivity estimated on the the two-digit industry level for production function $y = Ak^{\alpha}l^{1-\alpha}$. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Within TFP**

VARIABLES	(1) ΔTFP	(2) ΔTFP	(3) ΔTFP	(4) t+1 ΔTFP	(5) t+2 ΔTFP	(6) t+3 ΔTFP
real estate value	-0.000	-0.000	-0.010***	0.000	-0.003*	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	25,999	25,586	25,586	25,586	22,576	19,872
Adjusted R-squared	-0.032	-0.012	0.139	0.155	0.025	-0.012
Firm Fe	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	-	-	-	-	-
Industry*Year FE	-	Yes	Yes	Yes	Yes	Yes
Controls	-	-	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year	State*Year	State*Year

Note: For variable definitions see section B. Growth rates are log-differences. Columns (4)-(6) lead the dependent variable by 1, 2, and 3 periods. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Compustat: Industry TFP**

VARIABLES	(1) Δtfp	(2) Δtfp	(3) Δtfp	(4) Δtfp	(5) Δtfp	(6) Δtfp
Δ real estate	-0.060***	-0.066***	-0.075***	-0.075***	-0.072***	-0.062***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)
capital-labor ratio				0.009	-0.059	0.296
				(0.244)	(0.237)	(0.212)
sales growth					0.179***	0.128***
					(0.033)	(0.031)
return on assets						2.282***
						(0.151)
log(assets)						0.023**
						(0.009)
Observations	3,235	3,235	3,224	3,224	3,224	3,224
Adjusted R-squared	-0.019	0.005	0.059	0.059	0.080	0.190
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	-	Yes	-	-	-	-
2-digit*Year FE	-	-	Yes	Yes	Yes	Yes

Note: For variable definitions see section B. Growth rates are log-differences. 2-digit∗Year FE are time-varying fixed effects on the two-digit industry level. All variables are value added weighted averages on the four-digit industry level. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Compustat: Initial dispersion and misallocation**

VARIABLES	(1) full sample mean	(2) full sample covariance	(3) low disp. Δtfp	(4) high disp. Δtfp
Δ real estate	-0.007	-0.022**	-0.045	-0.112***
	(0.008)	(0.010)	(0.030)	(0.029)
Observations	3,282	3,175	1,077	1,073
Adjusted R-squared	0.785	0.454	0.148	0.184
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: or variable definitions see section B. Growth rates are log-differences. All variables are value added weighted averages on the four-digit industry level. *mean* and *covariance* denote unconditional industry productivity and covariance between firm size and firm productivity within each industry. *disp* stands for dispersion in initial real estate value, split into top and bottom tercile. All regressions include baseline industry controls. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **NBER manufacturing: Investment, labor, and TFP**

VARIABLES	(1) Δ investment	(2) Δ investment	(3) Δ employment	(4) Δ employment	(5) Δ TFP	(6) Δ TFP
Δ real estate	0.590***	0.565***	0.057**	0.115***	-0.082***	-0.086***
	(0.123)	(0.120)	(0.024)	(0.024)	(0.025)	(0.025)
skill ratio		-0.039		-0.108***		-0.042
		(0.171)		(0.038)		(0.031)
capital-labor ratio		-0.001***		-0.000***		-0.000
		(0.000)		(0.000)		(0.000)
log(energy)		0.063***		0.037***		0.012***
		(0.018)		(0.004)		(0.003)
Observations	7,256	7,256	7,256	7,256	7,256	7,256
Adjusted R-squared	0.009	0.031	0.001	0.256	0.005	0.102
Industry FE	-	Yes	-	Yes	-	Yes
Year FE	-	Yes	-	Yes	-	Yes

Note: For variable definitions see section B. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: **NBER manufacturing: Misallocation**

VARIABLES	(1) Δ low-skilled	(2) Δ high-skilled	(3) mean	(4) covariance
Δ real estate	0.119***	0.085*	-0.058**	-0.101
	(0.023)	(0.048)	(0.024)	(0.065)
Observations	7,256	7,256	320	320
Adjusted R-squared	0.244	0.059	0.932	0.619
Industry FE	Yes	Yes	-	-
2-digit FE	-	-	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: For variable definitions see section B. Growth rates are log-differences. All regressions include baseline industry controls. Columns (3) and (4) are value added weighted two digit industry averages. *mean* and *covariance* denote unconditional industry productivity and covariance between 4-digit industry size and industry productivity within each two-digit industry. 2-digit FE are fixed effects on the two-digit industry level. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 10: **MSA IV regressions**

VARIABLES	(1) First stage MSA hpi	(2) MSA IV long-term debt	(3) MSA IV investment	(4) MSA IV labor	(5) MSA IV $log(tfp)$
elasticity × mortgage	1.280***				
	(0.268)				
real estate value (MSA, IV)		0.180***	0.057***	0.024***	-0.036***
		(0.013)	(0.002)	(0.001)	(0.006)
Observations	10,193	37,173	37,173	36,280	23,039
Adjusted R-squared	0.875	0.429	0.438	0.684	0.636
MSA FE	Yes	-	-	-	-
Year FE	Yes	-	-	-	-
Firm FE	-	Yes	Yes	Yes	Yes
Industry*Year FE	-	Yes	Yes	Yes	Yes
MSA*Year FE	-	Yes	Yes	Yes	Yes
Cluster	MSA	MSA*Year	MSA*Year	MSA*Year	MSA*Year

Note: For variable definitions see section B. Column (1) depicts first-stage regression of MSA-level house price index on housing supply elasticity, interacted with country-wide 30-year mortgage rate. Columns (2)-(5) are second stage with MSA-level instrumented real estate value and include baseline controls. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: **Robustness**

VARIABLES	(1) non-tradable long-term debt	(2) tradable long-term debt	(3) service long-term debt	(4) manufacturing long-term debt	(5) perm. sample long-term debt	(6) skilled workers p(10)-p(90) long-term debt	(7) skilled workers p(25)-p(75) long-term debt
real estate value	0.174***	0.151***	0.111***	0.175***	0.140***	0.161***	0.192***
	(0.029)	(0.027)	(0.023)	(0.018)	(0.017)	(0.015)	(0.021)
Observations	19,406	12,156	20,246	28,079	27,749	38,157	22,486
Adjusted R-squared	0.402	0.450	0.452	0.412	0.373	0.434	0.411
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year	State*Year	State*Year	State*Year

Note: For variable definitions see section B. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 12: **Bank specialization**

VARIABLES	(1) full sample loans/assets	(2) not specialized loans/assets	(3) specialized loans/assets	(4) full sample loans/assets	(5) full sample loans/assets
real estate value	0.238***	0.363***	0.138***	0.330***	0.524***
	(0.022)	(0.053)	(0.043)	(0.036)	(0.055)
specialized US				1.051***	0.923***
				(0.078)	(0.166)
RE × specialized US				-0.140***	-0.247***
				(0.033)	(0.060)
Observations	34,649	9,573	6,712	18,708	16,467
Adjusted R-squared	0.605	0.668	0.719	0.651	0.740
Bank*Firm FE	-	-	-	-	Yes
Firm FE	Yes	Yes	Yes	Yes	-
Industry*Year FE	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year	State*Year

Note: For variable definitions see section B. *loans/assets* is syndicated loan volume standardized by firm fixed assets. *specialized* is a dummy based on banks' industry loan shares. *not specalized* and *specalized* denote bottom and top tercile of bank specialization. Values in parentheses denote cluster-robust standard errors. Industry∗Year FE are time-varying fixed effects on the four-digit industry level. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 13: **Firm productivity**

VARIABLES	(1) not specialized loans/assets	(2) specialized loans/assets	(3) not specialized loans/assets	(4) specialized loans/assets
real estate value	0.343***	0.084	0.280***	0.044
	(0.060)	(0.052)	(0.068)	(0.068)
RE × firm productivity	0.212**	0.292***		
	(0.086)	(0.082)		
RE × firm productivity (50)			0.328***	0.371***
			(0.121)	(0.124)
Observations	9,812	5,886	9,812	5,886
Adjusted R-squared	0.669	0.748	0.669	0.748
Firm FE	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year

Note: For variable definitions see section B. *loans/assets* is syndicated loan volume standardized by firm fixed assets. *productivity* are average firm productivity percentiles. *not specalized* and *specalized* denote bottom and top tercile of bank specialization. Values in parentheses denote cluster-robust standard errors. Industry∗Year FE are time-varying fixed effects on the four-digit industry level. Key: *** p<0.01, ** p<0.05, * p<0.1.

B Variable definitions

Table 14: **Variable definitions: Compustat**

variable	**formula**	**comment**
investment	capx/ppent$_{t-1}$	
long-term debt	ltdebt/ppent$_{t-1}$	
sales	sale/ppent$_{t-1}$	
labor	emp/ppent$_{t-1}$	
size	log(at)	log(total assets)
market-to-book ratio (q)	(at + (prcc $\times$ csho) - ceq - txdb)/at	
return on assets (ROA)	(opid - depam)/at	
sales growth	ln(sale$_t$) - ln(sale$_{t-1}$)	
payout ratio	(dvt + prstkc)/oibdp	
fixed assets	ppe	
employees	emp	
buildings	fatb + fatc	buildings and construction
land	fatp	
value added	sale - materials	
materials	(sale - oibdp) - emp $\times$ wage index	wage index from SSA
capital	ppent	
capital-labor ratio	ppent/emp	
S&P credit rating	spcsrc	
property sales	sppe	
tfp	$ln(y) - \alpha\ ln(ppe) - (1-\alpha)\ ln(emp)$	on 2-digit SIC, year FE
lp	value added / employees	labor productivity
tfp$_{OP}$	TFP	Olley and Pakes (1996)
tfp$_{LP}$	TFP	Levinsohn and Petrin (2003)
Δtfp	$ln(tfp_t) - ln(tfp_{t-1})$	TFP growth rate

Additional variables to indicate financial constraints:

- Kaplan-Zingales index:

$$-1.002 \times (ib + dp)/at_{t-1} - 39.368 \times (dvc + dvp)/at_{t-1} - 1.315 \times che/at_{t-1}$$
$$+3.139 \times ((dltt + dlc)/(dltt + dlc + seq)) + 0.283 \times q$$

- Whited-Wu index:

$$-0.091\times(ib+dp)/at_{t-1} - 0.062\times(dvc+dvp)DIVPOS + 0.021\times((dltt+dlc)/(dltt+dlc+seq))$$
$$-0.044 \times ln(at) + 0.102 \times ISG - 0.035 \times sales\ growth$$

  where: DIVPOS is a dummy equal one if firms paid dividends in year t, and ISG is industry sales growth

I define five metrics of financial constraints: payout ratio, firm size, bond rating, KZ and WW index (payout, KZ, and WW winsorized at 2.5th and 97.5th). For each variable, I group firms into lower and upper four percentiles for each year. A firm is defined as constrained if:

- its payout is low
- it is small
- it has a high KZ or WW index value
- it has no bond rating and positive long-term debt.

Table 15: **Variable definitions: NBER manufacturing**

variable	**formula**	**comment**
investment	invest/cap$_{t-1}$	
employment	emp	
real estate	plant/cap$_{t-1}$	structures
skill ratio	(emp-prode)/emp	share of non-production workers
capital-labor ratio	cap/emp	
energy	energy	
low-skilled	prode	production workers
high-skilled	emp-prode	non-production workers
capital	cap	
ΔTFP	dtfp4	four-factor productivity growth

Online Appendix to:

Collateral, Reallocation, and Aggregate Productivity
Evidence from the U.S. Housing Boom

C Online Appendix

C.1 Further Figures and Tables

Distortions and dispersion In their seminal paper, Hsieh and Klenow (HK, 2009) develop a framework to identify distortions, or wedges, to firms' capital and labor inputs. It is widely used to quantify productivity losses from misallocation (Pagés, 2010). In their model, marginal revenue products of capital and labor, as well as revenue productivity, should equate across firms if there are no distortions. The idea is that more productive firms will have higher output, which reduces the price of their good proportionally, such that higher productivity and lower price offset each other. Building on this benchmark, any dispersion in revenue products or revenue productivity must reflect firm-specific distortions and thus inefficiencies arising from misallocation. [31]

To back out distortions one must rely on strong assumptions about the market structure, firm-specific mark-ups, as well as the elasticity of prices in response to productivity shocks. Specifically, prices react much less than assumed to changes in productivity.[32] I develop a simple, but more general, empirical implementation that focuses on the capital-labor ratio, which allows me to identify changes in frictions affecting capital *relative* to labor. It does not require assumptions about mark-ups or price responses. Using the HK framework with output and capital wedges and solving the firm problem

$$\pi_{ist} = (1-\tau^y_{ist})(A_{ist}k^{\alpha_s}_{ist}l^{1-\alpha_s})^{\frac{\sigma_i-1}{\sigma_i}} - w_{st}l_{ist} - (1+\tau^k_{ist})R_{st}k_{ist},$$

the capital-labor ratio is given by

$$\frac{k_{ist}}{l_{ist}} = \frac{\alpha_s}{1-\alpha_s}\,\frac{w_{st}}{R_{st}}\,\frac{1}{1+\tau^k_{ist}}, \tag{10}$$

where i is firm, s is industry, and t time. τ^k denotes a capital-specific distortion relative to labor. An increase in τ^k makes capital relatively more expensive and reduces the capital-labor ratio. Without distortions (and mark-ups) we are back in the standard case and k/l is solely determined by industry variables. Note that firm-specific mark-ups and prices cancel out. Taking the logarithm, the log capital labor ratio is given by

$$ln\left(\frac{k_{ist}}{l_{ist}}\right) = ln\left(\frac{\alpha_s}{1-\alpha_s}\right) + ln\left(\frac{w_{st}}{R_{st}}\right) - ln\left(1+\tau^k_{ist}\right), \tag{11}$$

which can be expressed as a standard OLS regression

$$y_{ist} = \beta\ X_{st} + \epsilon_{ist} \tag{12}$$

where $y = ln(k/l), \epsilon = -ln\left(1+\tau^k\right)$, and X is a vector of industry-level variables w, R, and α. Thus, firms' capital-labor ratio can be decomposed into an aggregate (X) and idiosyncratic part (ϵ). The aggregate part depends on industry values of wages, rental rates, and the production function. The idiosyncratic part reflects relative distortions on

[31] Note that what matters for efficiency is the dispersion across firms within an industry, not the absolute level of a distortion for a given firm

[32] Recent work casts doubt on the accuracy of these assumptions, as well as the underlying data used (Foster, Grim, Haltiwanger and Wolf, 2017; Rotemberg and White, 2017).

capital inputs.

I implement equation (12) empirically by regressing $ln\left(\frac{k}{l}\right)$ on a set of industry-year dummies. The latter absorb any time-varying characteristics within each industry-year pair that affect firms' log capital-labor ratio. Fixed effects allow me to remain agnostic about values for capital coefficients, wages and rental rates, and other (unobserved) variables that affect industry capital-labor ratios. The residuals ϵ are then firm specific characteristics (distortions) that determine the deviation of capital-labor ratios from industry averages. Regressing y_{ist} on $\hat{X}_{ist}$ yields an R^2 of 0.4, while regressing y_{ist} on $\hat{\epsilon}_{ist}$ yields an R^2 of 0.6. Thus, about two-thirds of the variation in firms' capital-labor ratios *across* firms within an industry are explained by distortions.

Figure 8 shows that there is significant dispersion in capital-labor ratios, as well as distortions across firms. Firms in the top 10^{th} (5^{th}) percentile relative to the bottom 10^{th} (5^{th}) in terms of capital-labor ratios use 16 (43) times as much capital per employee, while distortions vary by a factor of 8 (18). If constraints are asymmetrically relaxed for firms, then we expect the dispersion of distortions to increase over time. I compute the standard deviation of ϵ within each industry-year pair for the full sample. Additionally, following the reasoning laid out in section 3.2, I split industries into top (bottom) tercile according to their initial 1993 variation in real estate values across firms. Findings above showed that industries in the top tercile see an asymmetric relaxation of financial constraints and suffer from misallocation. Hence, they should see an increase in dispersion of distortions, while for industries in the bottom tercile there should be no change.

Figure 4 plots the yearly median for each series. The solid line shows that for the full sample dispersion increased. Splitting the sample into industries with high (dashed line) and low (dotted line) variation in initial real estate values, shows that the increase is driven by higher dispersion within industries that suffered more from misallocation. The dashed line for industries with low variation in initial real estate value is downward trending. Thus, rising real estate value asymmetrically relaxes firms' financial constraints, which increases dispersion in distortions and lowers productivity through misallocation.

Regressing $log(k/l)$, as well as distortions ϵ, on real estate value in Table 23 yields a significant negative coefficient. Increasing real estate value by one standard deviation reduces firms' capital-labor ratio by 9.5 % in column (1), where I include baseline controls and firm and year fixed effects. Distortions ϵ decline by 14.2 % to 8.3 % (columns (2) to (4)), depending on the specification. Including controls in column (4) reduces the coefficient significantly. As $\epsilon = ln(\frac{1}{1+\tau^k})$, relaxing collateral constraints increases the cost of capital relative to labor, and thus τ^k. This means that firms' increase in employment is stronger than their increase in investment when collateral constraints are relaxed. This is in line with firm-level regressions in Table 3, where a one standard deviation increase in real estate value increases investment by 0.17 sd and employment by 0.20 sd.[33] Interestingly, this implies that looser financial constraints affect capital and labor to a different degree. It is therefore misleading to assume that financial constraints affect the allocation of capital alone.

[33]The discrepancy is even stronger when I exclude firms with zero real estate, where investment increases by 0.29 sd and employment by 0.37 sd.

Loan supply Over the last twenty years banks increasingly relied on collateralized lending (Flannery and Lin, 2016; Chakraborty, Goldstein and MacKinlay, 2018). If banks are more willing to lend to real estate owning firms independently of the increase in individual firms' real estate value, results are driven by credit supply effects. Instead, if rising real estate values relax financial constraints, firms' credit demand increases. Detailed syndicated loan market data on the firm-bank-year level allows me to control for changes in the financial sector through time-varying fixed effects at the bank level (Khwaja and Mian, 2008; Jiménez, Ongena, Peydró and Saurina, 2014). Absorbing bank-specific changes identifies the effect of increasing real estate value on firm characteristics not driven by supply effects. In addition, I decompose loan growth into supply and demand factors, following Amiti and Weinstein (2017).

For a sample of 3,292 firms and 2,058 banks I match 147,778 syndicated loans from 1995-2008. Syndicated loans are issued jointly by a group of banks to a single borrower. A lending syndicate entails at least one lead bank, which assesses the quality of the borrower, as well as other participating banks. Lead banks negotiate the terms and conditions of each loan and also monitor the borrower while the loan is active. Compared to other types of bank lending syndicated loans are on average bigger in volume, issued to large borrowers, and often used to diversify credit risk. Total syndicated lending increased from about 500 billion U.S. Dollars in 1990 to a peak of nearly five trillion U.S. Dollars in 2007. It is a major source of financing for many large US companies. Dealscan provides exhaustive information on transactions, including the issuing syndicate of banks and borrowing firm, outstanding amount, maturity, and interest rates. Additionally, it provides information on firms' and banks' type, location, and industry.

To allocate loan portions of transactions I split up the loan facility on a pro-rata basis among all participating banks in the syndicate.[34] I remove transactions with deal status 'canceled'. Total outstanding loan volume is calculated as the sum of the value of all outstanding loans that a firm has from a bank in a given year. All loans are kept active until maturity. I then standardize firms' total outstanding loan volume by lagged fixed assets and winsorize at the 1^{st} and 99^{th} percentile each year. All regressions include baseline controls and fixed effects. To highlight unobservable time-varying characteristics on the bank level, I subsequently add fixed effects varying at the bank level.

Table 22, columns (1)-(3), show results for loan volume as dependent variable. An increase in firms' real estate value significantly increases loan volume. Subsequently adding bank-firm (column (2)) and bank-firm plus bank-year fixed effects (column (3)) leaves coefficients nearly unchanged. The former look at variation within a specific firm-bank connection, while the latter additionally absorb time-varying changes within each bank. Thus, bank-specific changes within a firm-bank connection explain only a small part (around 1 %) of the overall effect.

[Table 22 about here]

Absorbing supply effects through bank-year fixed effects assumes that each bank behaves in identically towards all borrowers. If banks shifted their lending model from one

[34] Literature sometimes focuses on lead arrangers. As the focus of my work is on firms and I absorb all bank-related changes through fixed effects, different ways to split loans make little difference.

type of borrower to another (i.e. real estate owning firms), fixed effects will miss it. As an additional way to rule out supply effects, columns (4)-(5) decompose syndicated loan growth into demand and supply factors, following Amiti and Weinstein (2017).[35] Changes in a firm's total loan growth between a bank-firm pair reflect changes in loan demand by firms, as well as loan supply by banks. Column (4) shows that rising real estate values significantly increase firms' loan demand, while column (5) shows that there is an insignificant effect on supply factors. In line with columns (1)-(3), results suggest that rising real estate values relax collateral constraints and thereby increase loan demand.

Housing as factor of production To estimate productivity, I assume a Cobb-Douglas production function of type $y_{ft} = a_{ft}\kappa_{ft}^{\alpha}l_{ft}^{1-\alpha}$, where $\kappa = k + h$. k is capital and h structures and land. If housing enters the production function separately, its true form is $y_{ft} = z_{ft}k_{ft}^{\alpha}h_{ft}^{\beta}l_{ft}^{1-\alpha-\beta}$ and true productivity is given by

$$ln(z) = ln(y) - \alpha\ ln(k) - \beta\ ln(h) - (1-\alpha-\beta)\ ln(l),$$

while estimated productivity is given by

$$ln(a) = \underbrace{ln(y) - \alpha\ ln(k) - \beta\ ln(h) - (1-\alpha-\beta)\ ln(l)}_{ln(z)} + \underbrace{\alpha\ ln(k) + \beta\ ln(h) - \alpha\ ln(k+h) - \beta\ ln(l)}_{bias}.$$

Estimating productivity a instead of z leads to a bias. The direction of the bias will depend on parameter values, but in general, for firms with high β and thus high shares of real estate, productivity will be overstated. This is, productivity would be even lower for real estate owning firms if $y_{ft} = z_{ft}k_{ft}^{\alpha}h_{ft}^{\beta}l_{ft}^{1-\alpha-\beta}$. To quantify the bias, I estimate $ln(y) = \alpha\ ln(\kappa) + (1-\alpha)\ ln(l)$ and $ln(y) = \alpha\ ln(k) + \beta\ ln(h) + (1-\alpha-\beta)\ ln(l)$, where $\kappa = k + h$, for the sample of real estate owning firms (53,706 obs).[36] Figure 9 shows productivity distributions under both specifications, winsorized at the 2.5th and 97.5th percentile. They look almost identical with a correlation of 0.95. The mean for the regression excluding housing is slightly, but insignificantly, higher. In conclusion, treating housing as a separate factor of production does not affect my estimates.

[Figure 9 about here]

Alternatively, housing can enter the production function as an imperfect substitute for capital in a CES-aggregator form: $y = z[\gamma k^{\rho} + (1-\gamma)h^{\rho}]^{\frac{\alpha}{\rho}}l^{1-\alpha}$. Then true productivity is given by

$$ln(z) = ln(y) - \frac{\alpha}{\rho}\ ln(\gamma k^{\rho} + (1-\gamma)h^{\rho}) - (1-\alpha)\ ln(l).$$

[35] For detailed methodology, see their paper. In principle, they impose an adding-up constraint that ensures that adding up individual supply and demand shocks matches aggregate growth rates. This is similar to a WLS regression of loan growth between bank b and firm f in year t on firm and bank dummies, where weights are lagged loan shares. This identifies loan supply and loan demand factors for each bank and firm. Summing supply factors across a firm's lenders yields firm-specific loan supply shocks.

[36] I define real estate as $fatb + fatc + fatp$ and $\kappa = ppent$.

Assume $\kappa = \gamma k + (1-\gamma)h$. Then estimated productivity is given by

$$\begin{aligned} ln(a) &= ln(y) - \alpha\ ln(\gamma k + (1-\gamma)h) - (1-\alpha)\ ln(l) \\ &= \underbrace{ln(y) - \frac{\alpha}{\rho}\ ln(\gamma k^{\rho} + (1-\gamma)h^{\rho}) - (1-\alpha)\ ln(l)}_{ln(z)} + \\ &\quad \underbrace{\frac{\alpha}{\rho}\ ln(\gamma k^{\rho} + (1-\gamma)h^{\rho}) - \alpha\ ln(\gamma k + (1-\gamma)h)}_{bias}. \end{aligned}$$

The bias disappears as $\rho \to 1$. For a wide range of parameter values for α, ρ, γ, the bias is negative and close to zero (around $10e^{-4}$).

Did firms acquire new structures? To check whether firms buy real estate when property prices rise, I define a dummy variable *buyer* that equals one if firms acquired real estate from year $t-1$ to t, and zero otherwise. An increase in firms' historical book value of real estate indicates that firms bought new structures, while a decrease implies selling or depreciation. I run logistic regressions of the form

$$buyer^{s}_{f,t} = \beta \cdot hpi^{s}_{t} + controls_{f,t} + \delta_f + \epsilon_{f,t}, \tag{13}$$

hpi^{s}_{t} is the house price index on state-level in year t, and controls include standard firm controls. All regressions use fixed effects on the firm level. Table 24, column (1), uses firm fixed effects and shows that firms are significantly less likely to buy structures when house prices rise. Once year fixed effects and controls are added in columns (2)-(3), the effect turns insignificant, with an odds ratio close to 1. In column (3), a one unite increase in house prices decreases the probability of buying real estate by 1.6 %. Columns (4) and (5) interact the house price index with measures of financial constraints. Results show that there is a significant decline in the probability of buying real estate for constrained firms. In column (5), an one unit increase in house prices reduces the probability of buying real estate by 2.5 % for financially constrained firms. As constraints are relaxed, firms reduce their share of real estate over total assets.

[Table 24 about here]

Industries driving results Figure 7 highlights that two industry subgroups stand out. First, high-tech industries have a significant positive relationship between real estate value and productivity. Potentially these industries require IT inputs and benefit from rapid productivity growth in the sector. Second, industries "not elsewhere classified", "miscellaneous", or "other" have a strong negative correlation. Establishments in this sub-sector are categorized by what, and not how, they produce. The lack of specialization might lead to higher dispersion in productivity and worse misallocation.[37]

[Figure 7 about here]

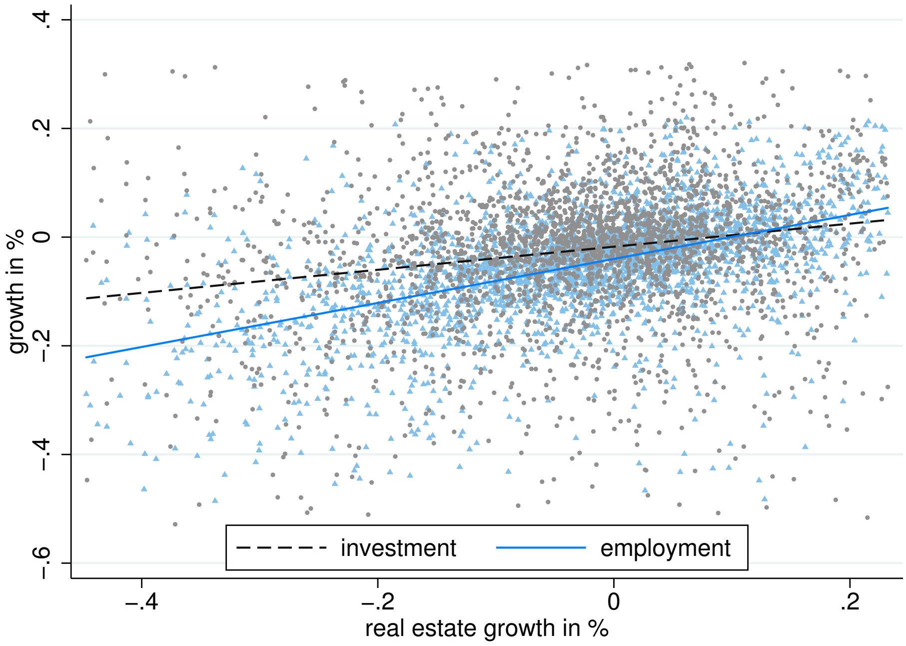
[37] To identify industries driving results I run equation (4) on the sample of industries with high initial dispersion and exclude industries one for one. Highlighted industries are amplifying/muting the effect by the most (top and bottom 5 %). For a list of industries, see Table 28.

Table 16: **Summary statistics for full sample**

Variable	Obs	Mean	Std. Dev.	P5	P10	P50	P90	P95
real estate value	48462	.57	1.06	0	0	.24	1.36	2.06
long-term debt	48462	.49	1.09	0	0	.07	1.41	3.14
investment	48462	.28	.21	.04	.07	.23	.6	.73
labor	47400	.08	.09	.01	.01	.04	.19	.29
log(TFP)	31613	.54	.17	.25	.32	.54	.73	.79
employees	47400	6414.44	26035.28	26	49	662	12401	27221
log(assets)	48462	4.64	2.14	1.33	1.97	4.55	7.49	8.32
leverage	48462	.28	1.09	0	0	.18	.55	.72
return on assets	48462	-.02	.3	-.62	-.33	.06	.18	.23
market-to-book ratio	48462	2.2	1.97	.75	.87	1.54	4.36	6.21
sales growth	48462	.12	.42	-.43	-.22	.09	.49	.75
Kaplan-Zingales index	48462	.92	2.25	-1.88	-.73	.86	2.73	3.82
Whited-Wu index	48431	-.22	.12	-.42	-.38	-.22	-.06	-.01

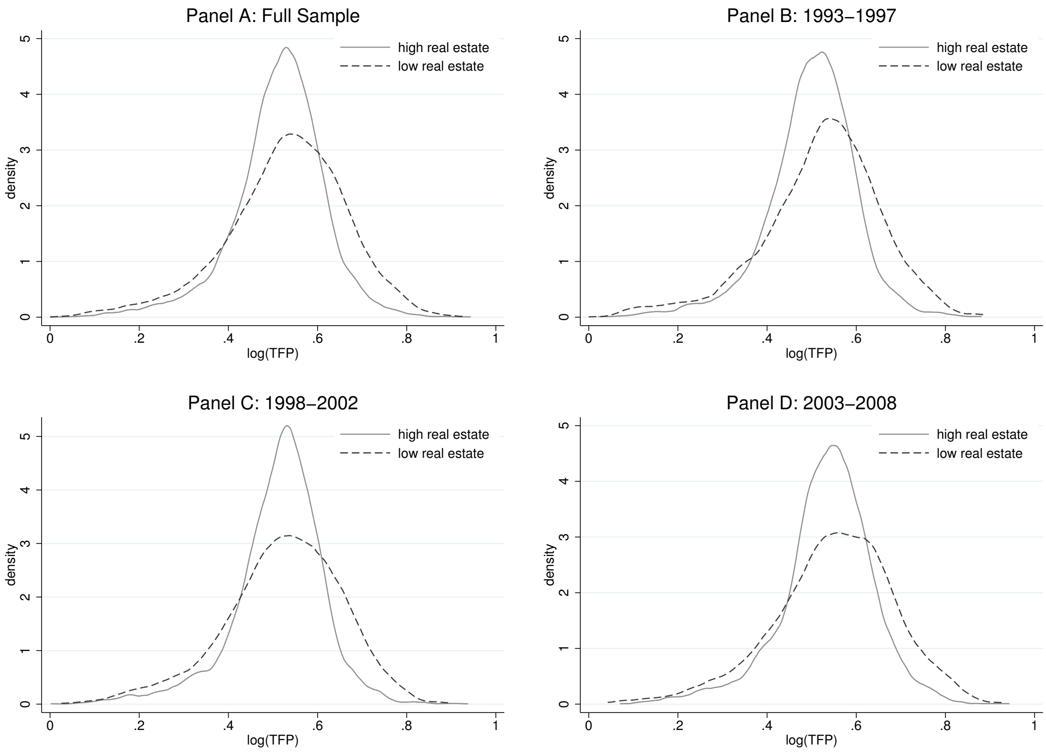
Note: For variable definitions see section B.

Figure 5: **Investment and employment**



Note: *investment* is defined as capital expenditure over lagged fixed assets, *employees* as employees over fixed assets. *realestate* is defined as value of structures and land standardized by lagged fixed assets (for details, see text). For illustrative purpose, growth rates are averaged log difference for each firm in sample. Correlations are almost identical for non-averaged sample. All variables winsorized at 2.5^{th} and 97.5^{th} percentile.

Figure 6: **Productivity**



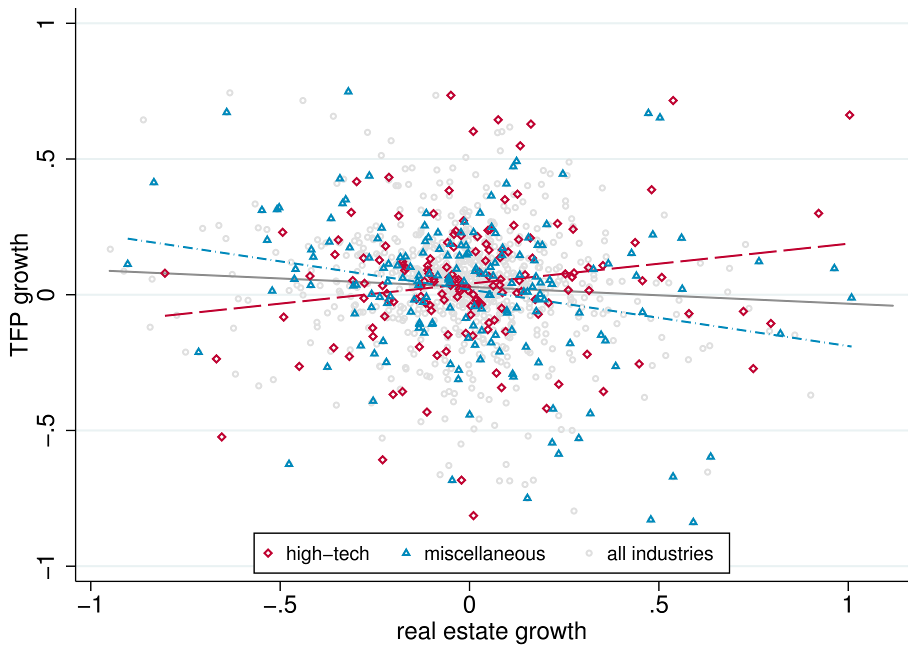
Note: $log(TFP)$ is log of total factor productivity estimated on the the two-digit industry level for production function $y = Ak^{\alpha}l^{1-\alpha}$. *high real estate* and *low real estate* denote top and bottom tercile of firm real estate value distribution. TFP is standardized to mean zero and variance one and conditional on industry fixed effects. *Full Sample* comprises all observations from 1993-2008.

Table 17: **Summary statistics by group (NBER manufacturing)**

	(1) **high RE** mean	sd	(2) **low RE** mean	sd	(3) **mean diff** t
real estate value	0.40	(0.12)	0.36	(0.09)	14.60
employment (in th.)	26.03	(42.02)	38.51	(57.01)	-8.67
capital (in m.)	2882.80	(6247.42)	3604.24	(8071.29)	-3.48
skill ratio	0.28	(0.12)	0.29	(0.12)	-1.93
capital-labor ratio	130.60	(139.50)	97.36	(101.60)	9.47
investment	0.07	(0.05)	0.09	(0.04)	-18.40
Δ real estate	0.02	(0.05)	-0.05	(0.07)	42.11
Δ investment	0.01	(0.40)	-0.04	(0.34)	4.94
Δ employment	-0.03	(0.10)	-0.03	(0.09)	-1.82
Δ low-skilled	-0.03	(0.11)	-0.03	(0.10)	-0.80
Δ high-skilled	-0.03	(0.16)	-0.02	(0.14)	-2.87
Δ TFP	-0.00	(0.07)	-0.00	(0.06)	0.05
TFP	1.15	(2.03)	1.14	(1.88)	0.10
Observations	2418		2419		4837

Note: Table 17 shows summary statistics by group for the NBER manufacturing sample. The full sample contains 458 industries with 7,256 industry-year observations. Industries with a high real estate share out of total assets are smaller in terms of total employment and assets, and operate with a lower skill intensity. They have lower capital-labor ratios and investment. There is no consistent difference in growth rates of investment, employment and TFP, except that high real estate industries have slower growth in skilled workers. For variable definitions see section B. Growth rates are log-differences. *high RE* and *low RE* denote top and bottom tercile of firm real estate value distribution. *mean diff* is t-value for difference in means.

Figure 7: **Industries driving results**



Note: For variable definitions see section B. High-tech industries are SIC codes 3575, 7990, 3663, 2731, 3829, 3842, 7900, 2835, 3851, 3530, 8051, 5072, 8060, 2741, 5160. non-classified are 8700, 5070, 8742, 5065, 2015, 3825, 2890, 3873, 3578, 5047, 2090, 3443, 3567, 3470, 2000. Industries are top and bottom 5 % of industries whose exclusion has strongest effect on coefficient of ΔRE on ΔTFP. All variables winsorized at 1^{st} and 99^{th} percentile, sample of high initial dispersion industries.

Table 18: **Financial constraints**

VARIABLES	(1) payout ratio long-term debt	(2) small firm long-term debt	(3) KZ index long-term debt	(4) WW index long-term debt	(5) bond rated long-term debt
real estate value	0.122***	0.009	0.116***	0.097***	0.146***
	(0.017)	(0.014)	(0.019)	(0.025)	(0.015)
RE × constrained	0.047***	0.194***	0.082***	0.067***	0.066*
	(0.015)	(0.021)	(0.021)	(0.023)	(0.034)
Observations	41,547	36,469	36,352	36,594	48,462
Adjusted R-squared	0.456	0.428	0.452	0.413	0.432
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year	State*Year

Note: To provide further evidence that rising real estate values relax collateral constraints, Table 18 interacts real estate value (RE) with different definitions of financial constraints. If rising asset prices work through the collateral channel, they should have a stronger effect on firms that face tighter constraints. The dummy *constrained* equals one if firms are constrained (for detailed definitions, see Section 14). The dependent variable is long-term debt. For all metrics of financial constraints, the coefficient on the interaction term is significant and positive. In line with theory, rising collateral value has stronger effects on constrained firms. For variable definitions see section B. *constrained* denotes different measures of financial constraints, as indicated by the column title. Each *constrained* is a dummy with value 1 if the firm is constrained, where constrained (unconstrained) is defined as the top (bottom) tercile for each respective category in each year. The only exception is *bond*, which takes value 1 if a firm has no bond rating. For details, see section B. Each regression includes the set of standard controls. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 19: **Productivity: Other metrics**

VARIABLES	(1) $log(lp)$	(2) $log(tfp)$	(3) $log(tfp_{op})$	(4) $log(tfp_{lp})$
real estate value	-0.036***	-0.034***	-0.021***	-0.025***
	(0.006)	(0.006)	(0.006)	(0.006)
market-to-book ratio	0.007	0.002	-0.020**	-0.009
	(0.007)	(0.007)	(0.008)	(0.008)
log(assets)	0.139***	0.076***	0.135***	0.039***
	(0.003)	(0.002)	(0.003)	(0.003)
return on assets	6.764***	6.948***	7.508***	7.301***
	(0.134)	(0.139)	(0.144)	(0.152)
sales growth	0.139***	0.147***	0.144***	0.163***
	(0.024)	(0.020)	(0.019)	(0.020)
Kaplan-Zingales index	-0.004	-0.010***	-0.005	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	31,278	31,278	31,278	31,278
Adjusted R-squared	0.619	0.636	0.941	0.906
Industry*Year FE	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year

Note: Table 19, column (1) uses labor productivity as dependent variable, column (2) our baseline TFP estimate (for comparison), and columns (3) and (4) estimates under Olley-Pakes and Levinsohn-Petrin. Coefficients are similar in sign, size and significance. $log(lp)$ is log of labor productivity, $log(TFP)$ is log of total factor productivity estimated on the the two-digit industry level for production function $y = Ak^{\alpha}l^{1-\alpha}$. $log(TFP_{op})$ is productivity estimated via Olley-Pakes, $log(TFP_{lp})$ via Levinsohn-Petrin. For variable definitions see section B. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 20: **Compustat: TFP alternatives**

VARIABLES	(1) Δlp	(2) Δtfp	(3) Δtfp_{op}	(4) Δtfp_{lp}
Δ real estate	-0.101***	-0.054***	-0.053**	-0.065***
	(0.025)	(0.017)	(0.023)	(0.024)
Observations	3,282	3,235	3,282	3,282
Adjusted R-squared	0.159	0.138	0.164	0.145
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: For variable definitions see section B. Growth rates are log-differences. All regressions include baseline controls. All variables are value added weighted averages on the four-digit industry level. $log(lp)$ is log of labor productivity, $log(TFP)$ is log of total factor productivity estimated on the the two-digit industry level for production function $y = Ak^{\alpha}l^{1-\alpha}$. $log(TFP_{op})$ is productivity estimated via Olley-Pakes, $log(TFP_{lp})$ via Levinsohn-Petrin. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 21: **Commerical real estate price index**

VARIABLES	(1) long-term debt	(2) investment	(3) labor	(4) $log(tfp)$
real estate value (commercial)	0.146***	0.026***	0.014***	-0.015***
	(0.014)	(0.002)	(0.001)	(0.005)
Observations	36,847	36,847	36,048	24,120
Adjusted R-squared	0.439	0.436	0.693	0.631
Firm FE	Yes	Yes	Yes	-
Industry*Year FE	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year

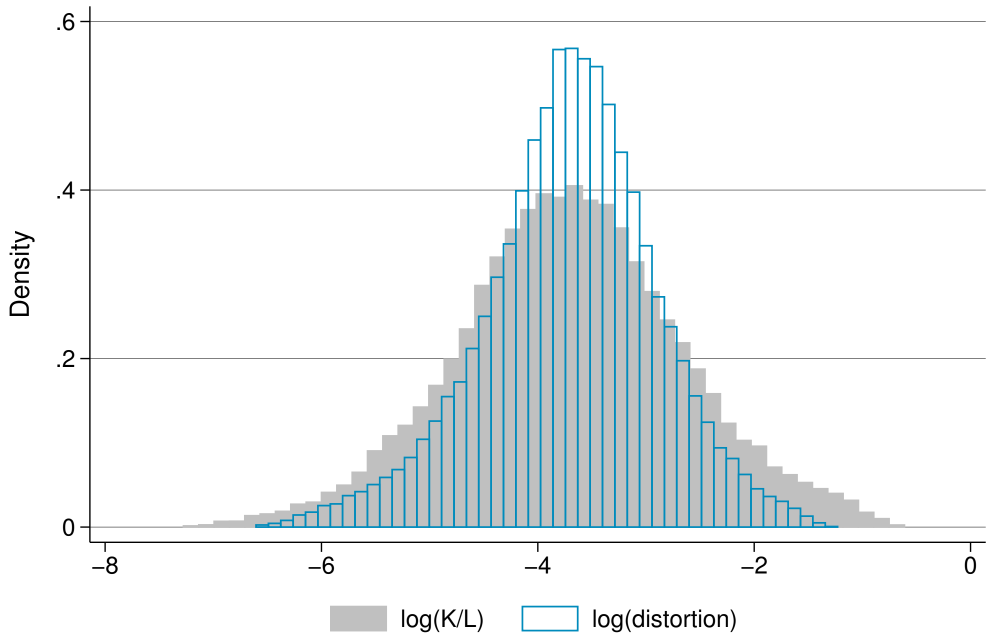
Note: For variable definitions see section B. *real estate value* is firm real estate value, inflated by census region commercial real estate prices. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 22: **Loan supply effects**

VARIABLES	(1) loan level bank loans	(2) loan level bank loans	(3) loan level bank loans	(4) firm level demand shock	(5) firm level supply shock
real estate value	0.196***	0.196***	0.194***	0.033**	-0.003
	(0.017)	(0.017)	(0.018)	(0.015)	(0.006)
Observations	144,352	144,352	137,707	4,108	4,108
Adjusted R-squared	0.835	0.835	0.831	0.599	0.980
Firm FE	Yes	-	-	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Firm*Bank FE	-	Yes	Yes	-	-
Bank*Year FE	-	-	Yes	-	-

Note: For variable definitions see section B. *bank loans* is syndicated loan volume standardized by lagged fixed assets. *demand* and *supply shock* are Amiti-Weinstein demand and supply components of a weighted least squares regression of loan growth on firm and bank dummies. For computational efficiency I focus on the largest 200 banks by loan volume in columns (4) and (5), which cover 97 % of total loan volume in the loan level sample. Time FE are fixed effects varying on the industry-year level (columns (1)-(3)) and (to maintain a reasonable sample size) yearly level (columns (4)-(5)). Columns (1)-(3) are on the firm-bank-year level (loan level), while columns (4)-(5) are on the firm-year level. Key: *** p<0.01, ** p<0.05, * p<0.1.

Figure 8: **Capital-labor ratio distribution**



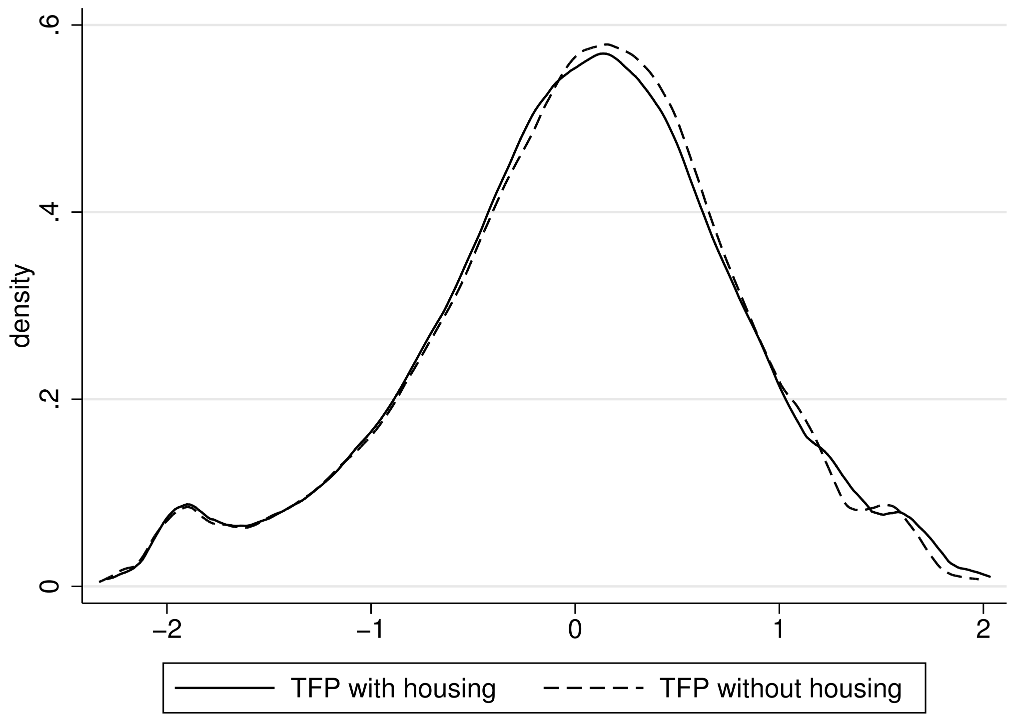
Note: Histogram of log capital-labor ratios, where capital is defined as *ppent* and labor as *emp*. *log (distortions)* refers to the residual of a regression of *ln(k/l)* on industry-year dummies.

Table 23: **Distortions and financial constraints**

VARIABLES	(1) log(k/l)	(2) distortion	(3) distortion	(4) distortion
real estate value	-0.095***	-0.142***	-0.147***	-0.083***
	(0.006)	(0.005)	(0.005)	(0.005)
Observations	47,420	52,761	52,761	47,367
R-squared	0.848	0.726	0.726	0.755
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	-	Yes	Yes
Controls	Yes	-	-	Yes

Note: For variable definitions see section B. Robust standard errors in parentheses. Baseline controls defined in 2. *Distortion* is residual of a regression of firms' log capital-labor ratios on industry-year dummies. Key: *** p<0.01, ** p<0.05, * p<0.1.

Figure 9: **TFP densities**



Note: For variable definitions see section B.

Table 24: **Buying real estate**

VARIABLES	(1) buys RE	(2) buys RE	(3) buys RE	(4) KZ index buys RE	(5) payout buys RE
house price index	-0.143***	-0.006	-0.017	-0.025	0.051
	(0.014)	(0.027)	(0.028)	(0.034)	(0.033)
hpi × constrained				-0.055***	-0.077***
				(0.020)	(0.018)
Observations	33,180	33,180	33,180	24,057	27,833
Number of firms	3,633	3,633	3,633	3,188	3,344
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	-	Yes	Yes	Yes	Yes
Controls	-	-	Yes	Yes	Yes

Note: For variable definitions see section B. Logistic regressions, dependent variable *buys RE* is a dummy with value 1 if real estate increases compared to last year. Columns (4)-(5) use Kaplan-Zingales index and payout ratio as measures of financial constraints. All regressions include firm and/or year fixed effects and baseline controls. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 25: **Quantile regression: Allocation component**

VARIABLES	(1) cov. 10 %	(2) cov. 25 %	(3) cov. 50 %	(4) cov. 75 %	(5) cov. 90 %
Δ real estate	-0.875*	-0.094***	-0.022	-0.038**	0.001
	(0.471)	(0.031)	(0.018)	(0.018)	(0.127)
Observations	3,189	3,189	3,189	3,189	3,189
Number of groups	293	293	293	293	293
SIC FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

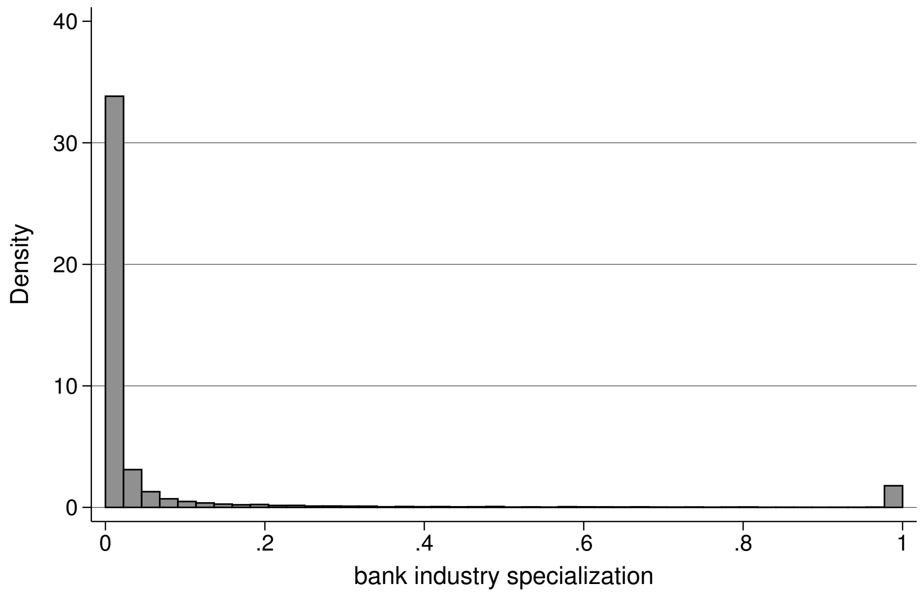
Note: For variable definitions see section B. Quantile regressions for different percentiles, including industry and year fixed effects, as well as controls for industry capital-labor ratios, and sales growth. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 26: **Buying real estate**

VARIABLES	(1) buildings	(2) land	(3) leases	(4) buildings	(5) land	(6) leases
firm age	0.039***	0.014***	-0.031***	0.080***	0.063***	-0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
firm age^2	-0.000***	0.000*	0.000	-0.001***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.478***	-1.420***	0.406***	-2.936***	-3.013***	-1.117***
	(0.068)	(0.073)	(0.073)	(0.144)	(0.153)	(0.215)
Observations	48,462	48,462	48,462	48,317	48,191	47,713
Industry FE				Yes	Yes	Yes
Controls				Yes	Yes	Yes

Note: Table 26 confirms the results with probit regressions. Columns (1)-(3) use firm age and firm age squared as explanatory variables. Columns (4)-(6) repeat the exercise, while controlling for firm size, return on assets, as well as industry dummies. In all regressions, older firms are more likely to hold buildings and land, and less likely to own capitalized leases. The negative coefficient close to zero on squared age for buildings and land implies that the effect decreases as firms mature. For variable definitions see section B. This table shows probit regressions with the probability of buying certain assets as dependent variable. *firm age* is firms' age as of 2017. Key: *** p<0.01, ** p<0.05, * p<0.1.

Figure 10: **Specialization**



Note:

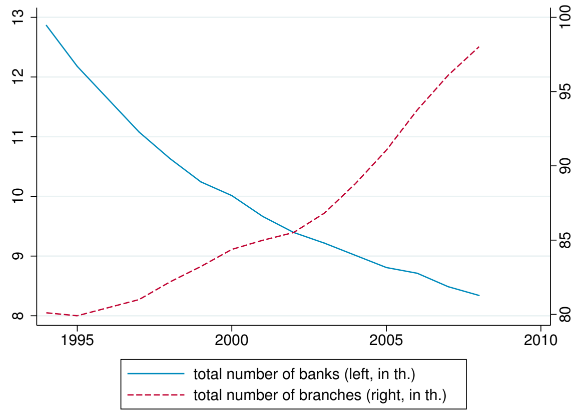
Table 27: **Summary statistics by specialization**

	not specialized		**specialized**		**mean diff.**
	mean	sd	mean	sd	t
loans/assets	1.71	(2.27)	1.41	(2.17)	8.25
real estate value	0.75	(1.23)	0.77	(1.32)	-0.97
log(assets)	5.55	(1.70)	6.01	(2.13)	-15.16
market-to-book ratio	1.71	(1.28)	1.85	(1.66)	-5.81
return on assets	0.07	(0.15)	0.04	(0.21)	11.22
investment rate	0.30	(0.31)	0.28	(0.31)	3.70
log(TFP)	-0.05	(0.73)	-0.05	(0.75)	0.48
Observations	8862		6867		15729

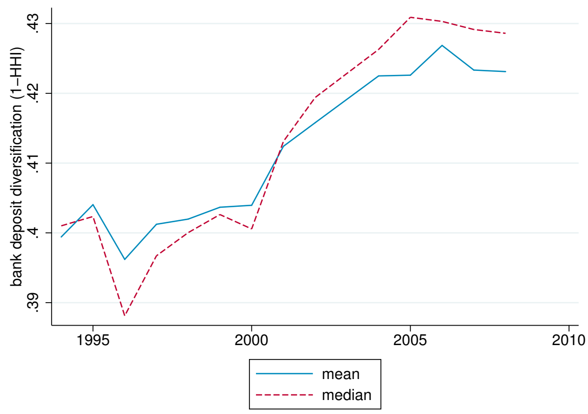
Note: For variable definitions see section B. *not specalized* and *specalized* denote bottom and top tercile of bank specialization. *mean diff* is t-value for difference in means.

Figure 11: **Banks expanded geographically**

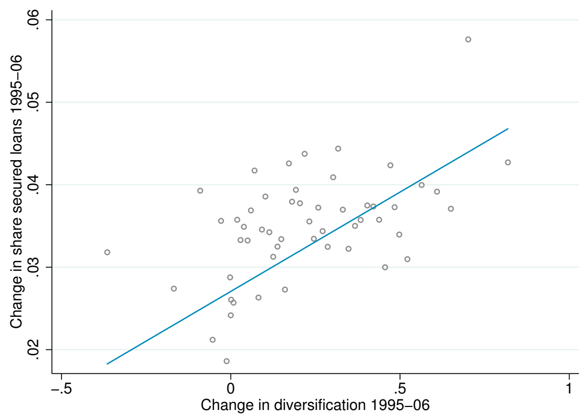
(a) Banks vs. branches



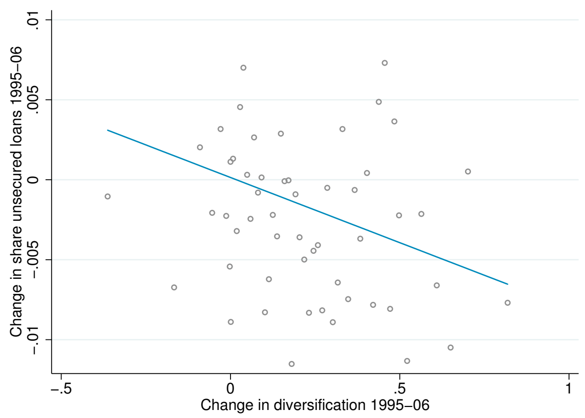
(b) Bank deposit diversification



(c) Δ secured loans vs Δ diversification



(d) Δ unsecured loans vs Δ diversification



Note: FDIC data provided by Summary of Deposits and Statistics of Depository Institutions. Diversification is computed as one minus Herfindahl index of bank deposit diversification across US counties. Secured (unsecured) lending denotes the share of commercial loans (not) secured by real estate out of total loans.

Table 28: **Sic codes**

SIC code	β **in %**	**SIC description**
3825	-13.4	instruments to measure electricity
2090	-8.1	miscellaneous food preparations & kindred products
5070	-7.9	wholesale-hardware & plumbing & heating equipment & supplies
3578	-7.4	calculating and accounting equipment
8700	-6.2	services-engineering, accounting, research, management
3567	-5.9	industrial furnaces and ovens
3873	-5.8	watches, clocks, watchcases, and parts
3470	-5.3	coating, engraving & allied services
5047	-4.9	medical and hospital equipment
2015	-4.8	poultry slaughtering and processing
3443	-4.8	fabricated plate work (boiler shop)
2000	-4.6	food and kindred products
8742	-4.1	management consulting services
2890	-3.8	miscellaneous chemical products
5065	-3.5	electronic parts and equipment, nec
8711	-3.3	engineering services
5122	-3.2	drugs, proprietaries, and sundries
5090	-3.1	wholesale-misc durable goods
3559	-2.9	special industry machinery, nec
3231	-2.8	products of purchased glass
3821	1.3	laboratory apparatus and furniture
3714	1.6	motor vehicle parts and accessories
3790	1.6	miscellaneous transportation equipment
5110	1.6	wholesale-paper & paper products
3577	2.1	computer peripheral equipment, nec
3851	3	ophthalmic goods
2741	3.1	miscellaneous publishing
2731	3.1	book publishing
5160	3.2	wholesale-chemicals & allied products
7990	3.5	services-miscellaneous amusement & recreation
5072	4.4	hardware
3842	4.9	surgical appliances and supplies
3530	5.7	construction, mining & materials handling machinery & equipment
3829	6	measuring and controlling devices, nec
2835	6	diagnostic substances
8060	6.2	services-hospitals
8051	6.2	skilled nursing care facilities
3663	7	radio and t.v. communications equipment
7900	10.1	services-amusement & recreation services
3575	21.4	computer terminals

Note: Top and bottom 20 industries with strongest effect on coefficient β in equation (4). β *in %* is relative change in β compared to coefficient on Δ *real estate* in Table 7, column (4). High (low) values indicate that excluding the industry weakens (strengthens) the effect.

Table 29: **Firm entry after 1993**

VARIABLES	(1) long-term debt	(2) investment	(3) labor	(4) value added	(5) log(TFP)	(6) log(LP)	(7) Δtfp
real estate value	0.335***	0.176***	0.028***	0.382***	-0.062***	-0.057***	
	(0.022)	(0.010)	(0.001)	(0.023)	(0.006)	(0.006)	
Δ real estate							-0.072***
							(0.017)
Observations	58,446	58,077	57,079	39,622	40,563	40,576	2,571
Adjusted R-squared	0.456	0.355	0.634	0.729	0.558	0.600	0.224
Firm FE	Yes	Yes	Yes	Yes	-	-	-
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	-
Industry FE	-	-	-	-	-	-	Yes
2digit*Year FE	-	-	-	-	-	-	Yes

Note: For variable definitions see section B. Columns (1)-(6) show firm level results for regression equation (2) for sample with firm entry after 1993; Column (7) industry results for equation (4). Firm level regressions cluster standard errors at the state-year level, industry regressions use robust standard errors. All regressions include baseline controls. Key: *** p<0.01, ** p<0.05, * p<0.1.
Sample details: The original sample contains 5,477 firms and 48,430 firm-year observations. Including firms that enter the sample after 1993 adds 2,158 firms and 9,994 firm-year observations. Firms entering are on average smaller, have a lower share of real estate, but higher investment rates and long-term debt. They also have higher levels of TFP.
Results are similar to baseline results. This reassures me that cohort effects and the changing composition of publicly held firms (driven by the IT sector during the 1990's) do not significantly alter results (Davis, Haltiwanger, Jarmin and Miranda, 2007; Decker, Haltiwanger, Jarmin and Miranda, 2016).

Table 30: **Effect of allocation on productivity**

VARIABLES	(1) t log(TFP)	(2) t+1 log(TFP)	(3) t+2 log(TFP)	(4) log(TFP)	(5) low disp. log(TFP)	(6) high disp. log(TFP)
covariance	0.050***	0.027***	0.007	0.052***	0.089***	0.033**
	(0.008)	(0.011)	(0.012)	(0.008)	(0.016)	(0.014)
Observations	3,538	3,258	2,977	3,526	1,021	1,018
Adjusted R-squared	0.778	0.759	0.756	0.811	0.805	0.812
Industry Fe	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	-	-	-
2-digit*Year FE	-	-	-	Yes	Yes	Yes
Controls	-	-	-	Yes	Yes	Yes

Note: This table shows that the allocation component has an effect on TFP. As increases in real estate value negatively affect allocation, they also affect TFP. For variable definitions see section B. Dependent variable in all columns is log(TFP), independent variable the intra-industry covariance between firm size and firm productivity. Columns (1)-(3) use industry and year fixed effects and lag the independent variable by one and two periods. There is a strong positive effect of resource allocation on productivity. A one standard deviation increase in allocative efficiency increases contemporaneous TFP by 5 %. The effect disappears after two years. Column (4) shows that the effect is robust to the inclusion of controls and time-varying fixed effects on the 2-digit industry level. In columns (5) and (6) *disp* stands for dispersion in initial real estate value, split into top and bottom tercile. The positive effect of allocation on TFP is only a third as strong for industries with high misallocation (those with high dispersion) in column (6). Key: *** p<0.01, ** p<0.05, * p<0.1. All regressions include robust standard errors.

Bank-firm relationships To further examine whether superior screening and monitoring helped in mitigating the credit boom fueled by rising real estate prices, I define the following metrics. First, for each firm I compute the yearly number of bank connections, i.e. how many distinct banks lend to each firm in each year. Under the assumption that firms that borrow from more banks are less opaque and better monitored, a higher number of firm-bank connection should make collateral less important. This is, firms with more bank connections should have a lower sensitivity of debt with respect to increases in collateral value. I define

$$connections_f = \text{average number of distinct lenders of firm } f$$

and dummy $connected_f$ that equals 1 if firms' number of bank connections (as measured by $connections_f$) is in the top tercile, and 0 if it is in the bottom tercile. Figure 12, panel 12a shows the distribution of firm lenders. The average (median) firm has 2.3 (2) lenders per year, with a standard deviation of 1.5 and a maximum of 17. Table 31 shows summary statistics. Note that splitting the sample by bank connections yields strikingly different groups compared to splitting the sample by banks' industry specialization.

Table 32 shows results. In line with the hypothesis, firms with more bank connections have a lower sensitivity of debt. This holds for a sample split (Columns (1) and (2)), as well as with interaction terms (Column (3)) and within each bank-firm connection in Column (4). Comparing columns (1) and (2), firms with few connections have a sensitivity that is five times larger than firms with multiple lenders.[38]

Finally, I make use of the robust finding in the literature that the duration of bank-firm relationships is important (Ongena and Smith, 2001; Berger and Udell, 2002). Over time, banks learn about firms' quality and adjust loan terms accordingly. Having a longer relationship with a bank should make a firm less responsive to changes in collateral. In other words, the earlier a firm and bank formed a relationship, the weaker firm debt should respond to increases in collateral values. To this end, I define:

$$relation_{f,b} = \text{length of firm-bank relation in years.} \tag{14}$$

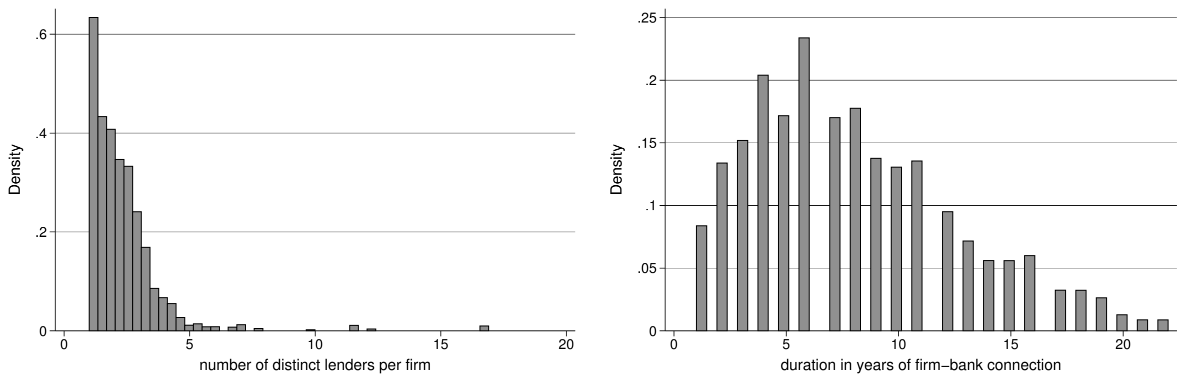
For the analysis, I focus on bank-firm connections with no breaks, i.e. continuous lending relationships between banks and firms. Figure 12, panel 12b shows the distribution of firm-bank relationships in years. The average (median) firm-bank relationship lasts 7.9 (7) years, with a standard deviation of 4.6 years and a maximum of 22 years. In line with above results, Table 32, columns (5) and (6), show that longer relationships mute the sensitivity of debt to increases in real estate value (negative coefficient on $RE \times relation$). This is true across and within individual firm*bank connections. Taken together, findings in this section suggest that well-informed banks mitigated the credit boom fueled by rising real estate prices. Related to Loutskina and Strahan (2011), the rapid geographical expansion of several banks during the boom period might have led to lax lending standards and thereby fueled the unsustainable lending boom.

[38]Note that his might be due to other reasons than bank connections per se. As shown in Table 31, firms with multiple bank connections are significantly larger and might have to rely less on credit by sheer size alone. However, reassuringly all three of my classifications yield similar results despite little overlap in sample groups. Additionally, using firm*bank fixed effects uses the variation *within* each firm-bank pair, which mitigates concerns that differences *across* firms drive findings.

[Figure 12 and Tables 31 and 32 about here]

Figure 12: **Connections and relations**

(a) Firm-Bank connections (b) Relation duration



Note:

Table 31: **Summary statistics by connections**

	few connections		**many connections**		**mean diff.**
	mean	sd	mean	sd	t
loans/assets	2.14	(2.57)	0.91	(1.63)	31.62
real estate value	0.64	(1.20)	0.85	(1.25)	-10.01
log(assets)	4.61	(1.58)	7.69	(1.57)	-112.80
market-to-book ratio	1.94	(1.85)	1.73	(1.02)	7.59
return on assets	0.01	(0.24)	0.10	(0.09)	-24.82
investment rate	0.35	(0.38)	0.24	(0.21)	20.14
log(TFP)	-0.13	(0.83)	0.09	(0.59)	-16.60
Observations	7639		5924		13563

Note: For variable definitions see section B. *few connections* and *many connections* denote bottom and top tercile of bank connections. *mean diff* is t-value for difference in means.

Table 32: **Firm connections**

VARIABLES	(1) few connections loans/assets	(2) many connections loans/assets	(3) full sample loans/assets	(4) full sample loans/assets	(5) full sample loans/assets	(6) full sample loans/assets
real estate value	0.528***	0.092***	0.418***	0.407***	0.326***	0.564***
	(0.096)	(0.032)	(0.058)	(0.077)	(0.042)	(0.073)
RE × connected			-0.317***	-0.230***		
			(0.066)	(0.082)		
relation					0.089***	
					(0.006)	
RE × relation					-0.006*	-0.019***
					(0.004)	(0.007)
Observations	4,379	11,571	17,293	16,132	20,795	18,940
Adjusted R-squared	0.655	0.505	0.644	0.733	0.611	0.717
Bank*Firm FE	-	-	-	Yes	-	Yes
Firm FE	Yes	Yes	Yes	-	Yes	-
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year	State*Year	State*Year

Note: For variable definitions see section B. *loans/assets* is syndicated loan volume standardized by firm fixed assets. *connected* is a dummy based on firms' average number of lenders. *few connections* and *many connections* denote bottom and top tercile of bank connections. *relation* denotes the length of a bank-firm lending relation in years. Values in parentheses denote cluster-robust standard errors. Industry∗Year FE are time-varying fixed effects on the four-digit industry level. Key: *** p<0.01, ** p<0.05, * p<0.1.

Geographic proximity of lenders Literature establishes that geographic proximity between borrower and lender facilitates acquiring soft information and leads to better access to capital (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010; Mandell and Wilhelmsson, 2015). The information banks acquire about their borrowers contains knowledge about value and quality of collateral, but also on profitability and efficiency. Cortés (2015) shows that "mortgage lenders with a physical branch near the property being financed have better information about home-price fundamentals than non-local lenders". My previous results documented that inefficient firms increased their borrowing when collateral values rise. If banks have better information about the underlying efficiency of firms, they should be more hesitant to lend to low quality borrowers (note that high real estate firms have lower ROA, productivity, and sales growth - even if productivity is not observable, ROA and sales growth are). In this section I will show that, for a given increase in real estate value, firms' borrowing increases by less if lenders and borrowers are geographically closer.

Building on a strand of literature that highlight the importance of geographic proximity in gathering hard and soft information, I define proximity in the following way. County data files provide information on the number of branches and offices, as well as bank deposits, in each county. I compute for each county the number of bank branches per capita (*proximity*), as well as average deposits per branch (*concentration*) and split counties into bottom and top tercile. Counties in the bottom tercile of proximity have fewer banks per capita, which I interpret as a larger distance between borrower and lender (I will call areas in the bottom tercile *remote* and the top tercile *close*). Similarly, counties in the top tercile of concentration are dominated by a few very large lenders with inferior information about borrowers.[39] The fact that real estate is mainly owned by inefficient firms yields the following hypothesis: Firms in counties with closer proximity between lenders and borrowers should see a lower sensitivity of borrowing in response to an increase in collateral value. The argument is that, if banks' know about a firm's underlying productivity, they are less willing to lend to unproductive firms against a given increase in collateral value.

To further investigate the role of information, I split my measure of real estate value into two components: buildings and land (separately inflated by state-level price indices). In general, land has lower loan-to-value (LTV) ratios than structures, as its market value is harder to verify (OCC, 2017). Additionally, the negative correlation between land value and log productivity is almost twice as large compared to total real estate value and productivity. This is, land is more information sensitive and land owning firms are inefficient, so the informational advantage of proximity should be greater for land than buildings.

Table 33 shows that the sensitivity of firms' long-term debt to higher real estate value is weaker in areas with close proximity between lenders and borrowers. All independent variables are standardized to mean zero and standard deviation one. Columns (1)-(2) use real estate value as explanatory variable. For a one standard deviation increase

[39] More banks could also imply higher competition, which theoretically could lead to more risk taking, but also prudence. Degryse and Ongena (2007) show that tougher competition leads to a stronger reliance on relationship lending, which, in this context, supports the idea that more banks per capita imply better information.

in real estate value, firms' long term debt increases by 35.2 cents in counties with low proximity in coulmn (1), and by 29.5 cents in counties with high proximity in column (2). The sensitivity is 0.352/0.295 = 1.19 times stronger in areas where lenders have poor information about borrowers (column (1)). Once I split real estate value into structures (columns (3)-(4)) and land ((5)-(6)), the general pattern remains. Increases in land value have a weaker effect on long-term debt, which likely reflects lower LTV ratios. Confirming the hypothesis, the ratio across county groups is 1.17 for buildings and 1.37 for land. The more information sensitive the underlying appreciating asset, the starker the difference in borrowing sensitivities across counties ranked by proximity. (In unreported robustness checks I show that results are similar for the *concentration* metric. Also, firms in areas with a higher share of savings banks see a stronger sensitivity of long-term debt to collateral value. This is likely due to the business model of savings banks, which rely mostly on residential and commercial mortgage lending. All results are robust to the addition of industry*year and state*year fixed effects.)

Table 33: **Banking concentration**

VARIABLES	(1) remote long-term debt	(2) close long-term debt	(3) remote long-term debt	(4) close long-term debt	(5) remote long-term debt	(6) close long-term debt
real estate value	0.352***	0.295***				
	(0.050)	(0.050)				
real estate value (structures)			0.394***	0.336***		
			(0.047)	(0.048)		
real estate value (land)					0.251***	0.185***
					(0.049)	(0.049)
Observations	10,438	10,461	10,415	10,358	10,438	10,452
Adjusted R-squared	0.494	0.502	0.496	0.503	0.489	0.499
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	State*Year	State*Year	State*Year	State*Year	State*Year	State*Year
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows that geographical proximity leads to a muted response of firms' long-term debt to rising real estate values. *remote* and *close* denote top and bottom terciles of counties with respect to number of banks per capita. For variable definitions see section B. Key: *** p<0.01, ** p<0.05, * p<0.1. All regressions include cluster-robust standard errors and baseline controls.

C.2 Spillover effects

Table 34: **Crowding out effects: local wages and employment**

VARIABLES	(1) Δ emp. exp.	(2) Δ emp	(3) Δ wage	(4) Δ emp. exp.	(5) Δ emp	(6) Δ wage
Δ house price index	0.207***	0.153***	0.056***	0.110***	0.071***	0.039***
	(0.020)	(0.018)	(0.005)	(0.011)	(0.008)	(0.005)
Observations	360,179	360,124	360,523	360,007	359,961	360,271
Adjusted R-squared	0.007	0.005	0.002	0.039	0.036	0.018
State*Time FE	-	-	-	Yes	Yes	Yes
Controls	-	-	-	Yes	Yes	Yes
Cluster	State	State	State	State	State	State

Table 35: **Crowding out effects: local wages**

VARIABLES	(1) Δ wage	(2) Δ wage	(3) Δ wage	(4) Δ wage	(5) no FIRE Δ wage
Δ house price index	0.056***	0.052***	0.049***	0.033***	0.028***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	360,523	360,051	359,801	359,801	254,957
Adjusted R-squared	0.002	-0.006	0.003	0.010	0.017
County*Naics FE	-	Yes	Yes	Yes	Yes
Time FE	-	-	Yes	-	-
State*Time FE	-	-	-	Yes	Yes
Controls	-	-	Yes	Yes	Yes
Cluster	State	State	State	State	State

Note: These tables show results for county-industry-year regressions. I use data provided by Quarterly Workforce Indicators to calculate county-industry level employment and wages. Results in Table 34 show that rising house prices lead to an increase in total employment expenditure that is driven by an increase in employment (3/4) and an increase in wages (1/4). Zooming in on wages, under the most stringent specification in Table 35, column (4), a 100 % increase in house prices increases local industry wages by 4.4 %. This suggests significant negative spillover effects. An increase in local house prices relaxes collateral constraints. Firms that own collateral expand and hire workers, which drives up wages. For firms that do not own collateral, the increase in labor costs likely negatively affects output. For variable definitions see section B. Key: *** p<0.01, ** p<0.05, * p<0.1. All regressions include cluster-robust standard errors.